Understanding riverine hydroecological response to climate change: Development of a coupled modelling framework

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ABSTRACT

Described as the most essential natural resource, rivers rank amongst those ecosystems most sensitive to climate change. The 2018 Brisbane Declaration highlights the pressing need to consider the resultant hydroecological impact. To this end, this thesis looks to develop a coupled hydrological-hydroecological modelling framework, an exciting first step under the new research agenda.

Initially, the focus lies on developing current understanding of the hydroecological relationship through consideration of potential delays in hydroecological response, alongside refinement of current modelling practice. There follows consideration of whether hydrological models can preserve ecologically relevant characteristics of the flow regime, as determined through hydroecological modelling efforts. Limiting factors are identified and an alternative hydrological modelling approach established. A holistic depiction of uncertainty is central to all developments.

The framework is developed with reference to a principal case study, the groundwater-fed River Nar, Norfolk; validation of the component models is achieved through additional case-studies. The hydrological model, forced with climate change projections, is used to simulate changes in the flow regime. This output then serves as input to the coupled hydroecological model. It is thus possible to assess the impact of climate change on hydroecological response in a quantitative manner.

Given data limitations, the framework is best suited to applications at the regional scale or by flow regime type. Its importance lies in the potential to inform water resources adaptation, as well as advancing the fields of hydroecological and hydrological modelling. Scope for further research centres around the wider socio-economic context, as recommended under the Brisbane Declaration.

Ter nagedachtenis aan mijn vader, Arjen Visser.

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Undertaking this PhD has certainly been an experience. Here follows a not-so-brief acknowledgement of some of the amazing people who have helped lighten the load.

I have to start with Will, my now husband. Thank you for marrying me so I can become Dr Quinn (engineering woman).

Mum, you have (always) been amazing. I couldn't have gotten this far without your love and support. You have only ever encouraged us to do what makes us happy. Also, thank you for proofreading the swathes of text towards the end – and for not charging!

This PhD only exists thanks to Professor Lindsay Beevers and her heroic efforts to secure funding. I am eternally grateful. Both Lindsay and Dr Sandhya Patidar have been tremendous supervisors. I was horrified in my first week when I was introduced to R by Sandhya; 4-years on, I couldn't live without it.

I chose to write this thesis through publication because I've wanted to be an academic for quite some time. The many reviewers' and editors' commentaries have had a transformative effect on the work (and a sometimes punitive effect on my state of mind). My thanks to them all (mostly). Thanks also to Colin Jones who got me started and was always there to answer my questions.

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A little bit of miscellanea to end. I can't not thank my four cats. You have brought cheer, madness and furballs to every minute. My final, and warmest thanks go to Lidl and Woodgate Pear Cider.

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Citation details	Visser, A., Beevers, L. and Patidar, S. (2017) Macro-invertebrate Community Response to Multi-annual Hydrological Indicators, *River Research and Applications,* 33(5), pp. 707–717. doi: 10.1002/rra.3125.		
Author 1, Annie Visser-Quinn née Annie Visser (AVQ)	*This declaration of contributor roles follow the MDPI Contributor Roles Taxonomy (CRediT).* AVQ came up with the initial **concept** based on the outcomes of previous work. AVQ undertook the **methodological development** and subsequent **investigation**. Both AVQ and SP undertook **computer coding**. **Visualisations** and the **draft manuscript** were prepared by AVQ; AVQ undertook all **revisions** to the text post-publication.		
Author 2, Lindsay Beevers	LB provided a **supervisory** role, providing guidance and mentorship. LB also **critically reviewed** the manuscript, and provided **commentary and feedback** pre and post-publication.		
Author 3, Sandhya Patidar	SP assisted with the initial writing of the **computer code**. Thereafter, SP took a **supervisory** role, providing guidance and mentorship. SP also **critically reviewed** the manuscript, and provided **commentary and feedback** pre and post-publication.		
Signature:	A.Quinn	[illegible]	Sandhya
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Author 1, Annie Visser-Quinn née Annie Gallagher Visser (AVQ)	*This declaration of contributor roles follow the MDPI Contributor Roles Taxonomy (CRediT).* AVQ is responsible for the **conceptualization** of the work and undertook the **methodological development** & subsequent **investigation** including the **computer coding**. **Visualisations** and the **draft manuscript** were prepared by AVQ, as well as **revisions** to the text post-publication.		
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ABBREVIATIONS

AR; AR4 or AR5	IPCC Assessment Report	Published by the Intergovernmental Panel on Climate Change (IPCC), an assessment report reviewing the state-of-the-art in climate change science. The fourth (AR4) and fifth (AR5) generations were published in 2007 and 2013/2014 respectively.
BFI	Baseflow Index	The proportion of flow derived from stored sources.
BIOSYS	Freshwater and Marine **Bio**logical **S**urve**y** for Invertebrate**s** England	The Environment Agency archive containing freshwater, river and make macroinvertebrate surveys.
CMIP	Coupled Model Intercomparison Project	Established by the World Climate Research Programme, the purpose of the Coupled Model Intercomparison Project is to establish a standard experimental protocol for studying the outputs of atmosphere-ocean climate models. Since the fifth generation, the IPCC Assessment Reports (AR) and CMIP have been aligned, i.e. AR5 considers CMIP5 projections, whereas AR4 maps to CMIP3.
DELHI	Drought Effect of Habitat Loss on Invertebrates	A recently developed biotic index to "track the ecological effects of drought development and recovery" (Chadd *et al.*, 2017) of the riverine macroinvertebrate community. The unweighted counterpart to the Lotic-Invertebrate Index for Flow Evaluation (LIFE).
ER HI	Ecologically relevant hydrological indicators	Hydrological indicators representing characteristics of the flow regime identified as being ecologically important, e.g. through a hydroecological model.
GRJ	Modèle du **G**énie **R**ural **J**ournalier	Suite of daily, n-parameter, lumped models developed by the INRAE Catchment hydrology research group.
IHA	Indicators of Hydrologic Alteration	A suite of ecologically relevant characteristics of the flow regime used to determine the impact of hydrologic alteration. (*Not* the Nature Conservancy software program of the same name.)
IPCC	Intergovernmental Panel on Climate Change	Jointly established by the World Meteorological Organisation and the United Nations Environment Programme. Intended to support policy-Design to inform policy interventions and climate change adaptation, the IPCC develops: • Assessment reports (AR), reviewing the state-of-the-art in climate change science; and, • Suites of future emissions scenarios, from which climate change project ions may be derived.

ISI-MIP	Inter-Sectoral Inter-comparison Project	An intercomparison project establishing a protocol for studying climate impact projections across different sectors and scales.
kBP	-	One thousand years before present.
LIFE	**L**otic-invertebrate **I**ndex for **F**low **E**valuation	A semi-quantitative biotic index; a function of known flow preferences and abundance-weighting (logarithm of the binned abundance). For further details, see Appendix A.
MC	Monte Carlo methods	Random, or quasi-random, sampling of a probability distribution for the purposes of uncertainty analysis.
MME	Multi-Model Ensemble	An ensemble of model simulations from a series of structurally different models. Can be used to determine structural uncertainty.
NSE	Nash Sutcliffe Efficiency	A measure of the goodness of fit relative to the 1:1 line (the observational mean).
PCA	Principle Component Analysis	Principal Component Analysis transforms (potentially) correlated variables into a series of linearly uncorrelated variables. In doing so, it is possible to identify duplicated data or redundant variables.
PPE	Perturbed parameter ensemble	Also known as a perturbed physics ensemble. An ensemble of model simulations from a series of model variants (of different parameterisations). Can be used to determine parameter uncertainty.
RCP	Representative Concentration Pathways	The third generation of climate change emissions scenarios developed by the Intergovernmental Panel on Climate Change (IPCC) for the fifth Assessment Report (AR5) in 2014. The pathways represent the radiative forcing by 2100; e.g. RCP 8.5 stabilises at 8.5 W/m^2.
RVA	Range of variability approach	Introduced in Richter *et al*. (1996; 1997), the RVA facilitated the comparison of pre- and post-impact conditions, thereby allowing the impact of hydrologic alteration to be quantified.
SRES	Special Report on Emissions Scenarios	A report detailing the second generation of climate change emissions scenarios developed by the Intergovernmental Panel on Climate Change (IPCC) in 2000. Supersedes IS92 from 1992.

UKCP	United Kingdom Climate Projections	Perturbed parameter ensembles of UK climate projections developed by the Met Office's Hadley Centre. UKCP09 represented the first generation of probabilistic climate projections for the UK; it considered scenarios from the Special Report on Emissions Scenarios (SRES) and the CMIP3 generation of Hadley Centre climate models. Superseding UKCP09, UKCP18 provides up-to-date projections, using the CMIP5 generation of Hadley climate models forced by the fifth assessment report Representative Concentration Pathways.

GLOSSARY OF TERMS

Adjusted R-squared, $\hat{R}$	R-squared, also known as the coefficient of determination, is a measure of the variance between the observed and simulated data. The adjusted R-squared is used in multi-variate linear regression to avoid overfitting.
Benthic macroinvertebrates	An invertebrate is a type of animal with no backbone; macroinvertebrate can be seen without the aid of a microscope. Benthic macroinvertebrate are bottom-dwelling aquatic macroinvertebrates. The terms are used interchangeably.
Bias	In mathematics, a systematic deviation, e.g. a positive bias represents an overestimation.
Bias correction	A type of correction applied to redress or minimise the influence of bias; commonly applied to climate projections.
Biodiversity	The variety in life. For the United Nations Convention on Biological Diversity definition, see *page 2*.
Brisbane Declaration	*See environmental flows.*
Catchment	A catchment, or basin, is an area of land over which precipitation drains into a common outlet such as a river or lake.
Climate, *change*	Weather reflects short-term atmospheric conditions, whilst climate is the long-term average weather. Climate change refers to a long-term change in the climate, this in turn has implications for weather.
Climate, *change impact model*	Climate change impact models facilitate decision-making by exploring how environmental change may impact a given sector or sectors.
Climate, *model*	A group of models used to model climate at the global or regional scale. Featuring in CMIP3, General Circulation Models consider an atmospheric composition changing at a fixed rate. A more complete representation of the earth system is provided in CMIP5 through Earth System Models, where the atmospheric composition is determined by emissions, feedbacks, and the closing of the carbon cycle.
Climate, *projections*	Estimates of the future climate, based on a series of assumptions (e.g. emissions scenario), which may or may not be realised.
Component model	Developed following a component-based development approach, a component model is one of a collection of models which represent a component of a larger model or system.

Ecosystem, *functionality*	The functionality or sustainability of an ecosystem; linked to biodiversity and the provision of ecosystem services. For further details, see *Figure 1-1*.
Ecosystem, *services*	The goods and services provided by the ecosystem. For the definition used in the book Nature's Services, see *page 3.*
Emissions scenario	A storyline or pathway of future emissions until 2100 and beyond.
Environmental flows	The minimum flows required to protect a river or freshwater ecosystem. For the Brisbane Declaration definitions, see *pages 4 and 8*.
Flow regime, *facets*	Facets of a river's flow regime - magnitude, duration, frequency, timing, and rate of change – which characterise the range of flows and hydrological events. See also *Table 1-1*.
Flow regime, *natural*	The natural unmodified flow regime of a river; characterised using the five facets of the flow regime.
Flow regime, *classification (or group or type)*	Rivers with (statistically) similar flow regime characteristics (as defined by the five facets of the flow regime).
Functional trait	The ecological role of a species. Functional diversity introduces redundancy into the system. See also *page 2.*
Hydroecology	Sometimes referred to as ecohydrology. The relationship between hydrology and ecology.
Hydroecological response	The ecological response to antecedent flows. Synonymous with *river health.*
Hydrologic alteration	Any form of alteration of the natural flow regime.
Hydrological model, *distributed*	A type of hydrological model which subdivides the catchment into a grid or mesh from which the relative flow contributions are determined.
Hydrological model, *lumped*	A type of hydrological model which considers the catchment as a singular unit.
Indicator, *biotic*	A biological indicator whose functional traits and preferences may be used as an indicator of environmental change.
Indicator, *flow exceedance*	A measure of the flow equalled or exceeded n% of the time, e.g. Q90 is the flow exceeded 90% of the time, a measure of low flow.
Intra-annual, inter-annual and multi-annual	Time periods over which hydrological indicators are measured: • *Intra-annual.* Occurring within a year; • *Inter-annual.* Occurring between or over two years; • *Multi-annual.* Occurring over a period of multiple years.
Information criterion	For model selection, a measure of quality.

Information theory	An information theory approach determines a quantitative measure of support for each candidate model. Inference is made from multiple models through model averaging (of parameter Akaike weights). For details, see *publication 2, Visser et al. (2018).*
Information theory, *importance*	A statistical measure of the importance of a variable. Importance is determined through ranking of the average parameter Akaike weight; the highest value represents the most important variable. For details, see *publication 2, Visser et al. (2018).*
Interspecific	Occurring between different species.
Lag (in ecological response)	A delay in the ecological response to flow extending beyond the immediately preceding season.
Model, *biophysical*	A representation of a biological system based on physical properties.
Model, *calibration*	Definition adopted in this thesis: Model parameterisation relying on objective functions and optimisation algorithms.
Model, *coupled* or *chain*	The joining together of two or more models. Models may be coupled offline, where the output of one model serves as the input to another; or online, where the models are run together and feedbacks between the models are accounted for.
Model, *evaluation*	Definition adopted in this thesis: Comparison of observed and simulated data assessing model performance; commonly termed *validation* in hydrological modelling.
Model, *parameterisation*	Definition adopted in this thesis: The tuning of a model to identify the optimal parameter set(s).
Model, *validation*	Definition adopted in this thesis: An assessment of the suitability or capability of a given model structure. For the assessment of model performance, see *model evaluation*.
Parsimony	The principle of parsimony, or Occam's razor, posits that a solution should be no more complex than necessary. In the context of modelling, model simplicity relative to performance is thus made key.
Efficiency criteria	A measure of model performance; synonymous with performance criteria. Examples include Nash Sutcliffe Efficiency (NSE).
Objective function	A function describing the objective of traditional algorithmic hydrological modelling. Objective functions are frequently represented by one or more efficiency or performance criteria.
Performance criteria	A measure of model performance; synonymous with efficiency criteria. Examples include Nash Sutcliffe Efficiency (NSE).

Future flows (or flow projections)	Forward projections of flows, derived from a hydrological model forced by a climate model.
p-value, p	Assuming that the null hypothesis is correct, the p-value is a measure of the probability that the effect seen is a product of random chance.
R	An open-source software environment and programming language.
R package	Community-developed packages of objects, such as functions and data, extending the capabilities of the R environment.
Resilience	Based on Lake (2013), the ability to recover from a disturbance.
Resistance	Based on Lake (2013), the capacity to withstand a disturbance.
River health	The condition of the river ecosystem, synonymous and, thus, used interchangeably with *hydroecological response*.
Season, *ecological*	Time periods relating to peak macroinvertebrate activity. For the UK context, defined as spring (Apr-Jun) and autumn (Oct-Dec).
Season, hydrological	The (approximately) 180-day time-periods over which the hydrological indicators are determined. For the UK context, this is summer (Apr-Sep) and winter (Oct-Mar).
Stationarity	The assumption that relationships hold constant in the long-term.
Stepwise selection	An algorithm adds and/or subtracts variables in steps, according to a specific criterion. The algorithm stops once the stopping criterion has been met, resulting in a single model output.
Stochastic	A stochastic process is a group or family of random variables.
Uncertainty	Uncertainty is the error introduced as a result of an imperfect representation of a real-world phenomenon.
Uncertainty, *epistemic*	Uncertainty either due to a lack of knowledge, or an ability to capture the requisite processes.
Uncertainty, *equifinality*	Uncertainty introduced due to equifinality: the presence of multiple best fit parameter sets. See also *parameter uncertainty.*
Uncertainty, *parameter*	Uncertainty in the values of the parameters in a model.
Uncertainty, *propagation*	The cascade of uncertainty through a modelling chain, e.g. from climate to hydrological to hydroecological model.
Uncertainty, *structural*	Uncertainty due to differences in model structure; a reflection of a lack of knowledge about the underlying physical mechanisms.
Weather generator	A stochastic weather generator produces synthetic time series of weather based on the statistical properties of observed weather.

CHAPTER 1. INTRODUCTION

This thesis provides a critical reflection on the author's contribution to hydroecological & hydrological modelling and projections, under a changing climate, therein. The main focus is on selected publications between 2017 and 2019. This introductory chapter begins by providing the background to the subject matter. A review of the state-of-the-art in the respective fields follows. The problem statement to be addressed, as well as the research questions, are thus established. This chapter then concludes with an outline of the overall thesis structure.

1. BACKGROUND

1.1 BIODIVERSITY

There is widespread nescience of the importance of biodiversity, ecology and ecosystems (Cork *et al.*, 2001; Pyle, 2003; Chivian and Bernstein, 2004; Dudgeon *et al.*, 2007). Within the public sphere, reasons for preserving biodiversity are, frequently, aesthetic, cultural and economic in nature (Loreau *et al.*, 2001). The importance of biodiversity cannot be understated; note the centrality of biodiversity depicted in Figure 1-1. Stability, functionality and the sustainability of ecosystems are all dependent upon biodiversity (Tilman, 1997). Further, inter-specific (between species) competition increases commensurate with diversity, leading to improved ecosystem productivity and the provision of other services (Tilman, 1997). Critically, the less diverse an ecosystem is, the more vulnerable it is to environmental change. Drivers of this change include demographic, management practices and climate change.

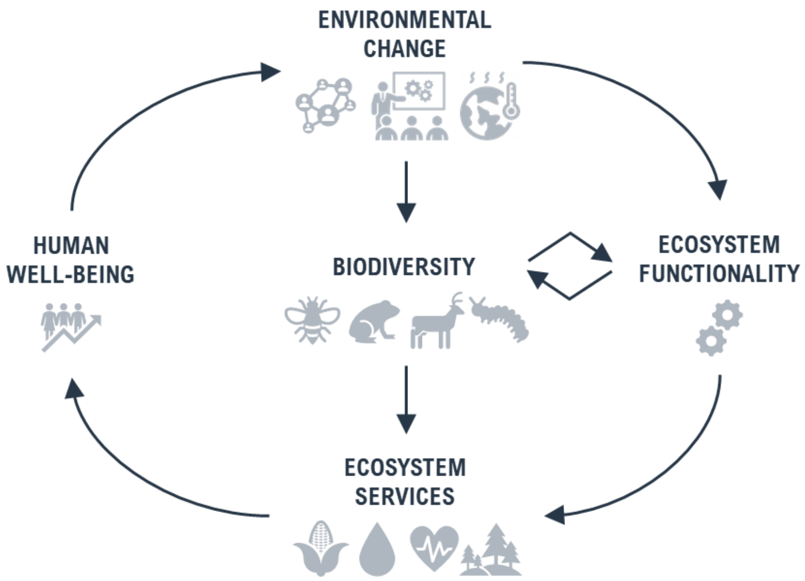

Figure 1-1. Conceptual framework showing the links between biodiversity, ecosystem functionality, ecosystem services, human well-being, and environmental change. Note: (1) how environmental change links to human well-being biodiversity and ecosystem *through* services; and (2) the feedback loop between biodiversity and ecosystem functionality. *Source: Annie Visser-Quinn. Based on Chapin et al. (1997), Cardinale et al. (2012) and Visser et al. (2019a).*

In order to understand why biodiversity matters, and what it does for us, it is necessary to first consider what biodiversity means. Swingland (2001), Morar *et al.* (2015), Toepfer (2019) highlight that there has been significant difficulty in arriving at a single definition of biodiversity. Frequently cited is the Convention on Biological Diversity (United Nations, 1992) definition: *"Biodiversity is the variability among living organisms, within & between species and ecosystems"*. Whilst there remains a level of ambiguity, there exists a wealth of literature focussing on the putative components of biodiversity and their implications for human welfare:

- *Species diversity.* A measure of the number and relative abundance of species (E.C., 1977; Noss and Cooperrider, 1994; Swingland, 2001);
- *Functional diversity.* Functional traits are those which define species in terms of their ecological roles, how they interact with the environment and other species (Díaz and Cabido, 2001); for example, herbivory and predation (Swingland, 2001). The probability that species with important functional traits are present is commensurate with the number of species in the community (Chapin *et al.*, 1997).

These interspecific differences increase the redundancy and hence resilience of the community;

- *Genetic diversity.* This is the adaptive capacity (natural selection) of the population to disturbance (Swingland, 2001);
- *Structural/community diversity.* The structure of the community refers to the age or life-stage of species as well as the organisation of the food web (Swingland, 2001; Hunter and Gibb, 2007). The loss of keystone species specifically, which occupy a critical role in the food web, can have a disproportionately large effect on ecosystem functionality, resilience and resistance (Chapin *et al.*, 1997).

1.2 ECOSYSTEM SERVICES

The goods and services provided by ecosystems are known as ecosystem services, defined by Daily in the seminal book Nature's Services (1997, p. 3) as: *"the conditions and processes through which natural ecosystems sustain and fulfil human life".* The Millenium Ecosystem Assessment (2005) describes four categories of intrinsically linked ecosystem services: *supporting services* which enable the delivery of *provisioning services*, the material products obtained from the ecosystem; *regulating services*, those which control ecosystem processes; and *cultural services*, which provide non-material benefits.

To illustrate the importance of rivers, Costanza *et al*. (1997) estimated that the value of these five services (below; provided by both rivers and lakes) was at least $1.7 trillion pa globally (equivalent to over $3.3 trillion pa today):

- *Flow regulation.* Such as minimum flows, flushing flows;
- *Water purification.* The dilution and breakdown of biological components;
- *Water supply.* Consumptive uses include irrigation, industrial and municipal/domestic water supply;
- *Food production.* Fishing represents direct provision, whilst rivers also support the provision of crops, nuts and fruit indirectly (through irrigation);
- *Recreation.* Instream activities include boating, fishing, and swimming. Activities may also be riverside, such as walking.

It is also worth highlighting that interaction with the surrounding environment supports a wide variety of riverine habitats and commensurate number of additional services (Jones *et al.*, 2013).

1.3 ENVIRONMENTAL FLOWS

In many parts of the world, rivers serve as the principal water resource. By supporting the most essential human needs, Meybeck (2003), Vörösmarty *et al*. (2005; 2010) and the World Water Assessment Programme (2009) posit that freshwater is the most essential natural resource. This has led to over-exploitation and the decline in health of freshwater ecosystems worldwide. Consequently, freshwater ecosystems are in crisis (Sanderson *et al.*, 2002; Vörösmarty, 2002; Dudgeon *et al.*, 2007; Butchart *et al.*, 2010; Vörösmarty *et al.*, 2010). In their global synthesis of threats to river and human water security, Vörösmarty *et al.*, 2010, estimated that, 65% of global river discharge, supplying 80% of the world's population (4.8 billion in 2010), is under threat. Further, in 2016, the World Wildlife Fund (WWF) estimated that, between 1970 and 2012, freshwater biodiversity declined by 81%, more than double that of terrestrial and marine combined. This human domination of the biosphere has been termed the Anthropocene, the human epoch (Crutzen, 2002; Zalasiewicz *et al.*, 2008). With escalating trends in human population, water use and development pressure, freshwater ecosystems are projected to remain under threat well into the future (Vörösmarty *et al.*, 2010).

The need to balance the conflicting demands of both human society and those of the ecosystem has seen the emergence of the environmental flow movement. Environmental flows are the minimum flows to protect river ecosystems (Arthington *et al.*, 2006). Under the 2007 Brisbane Declaration they are formally defined as:

> *"…the quantity, timing, and quality of water flows required to sustain freshwater and estuarine ecosystems and the human livelihood and well-being that depend on these ecosystems…".*

With reference to Figure 1-2, this section provides a synopsis of the development of the environmental flow concept and the underlying hydroecological principles; note, particularly, the central role of Australia and Europe.

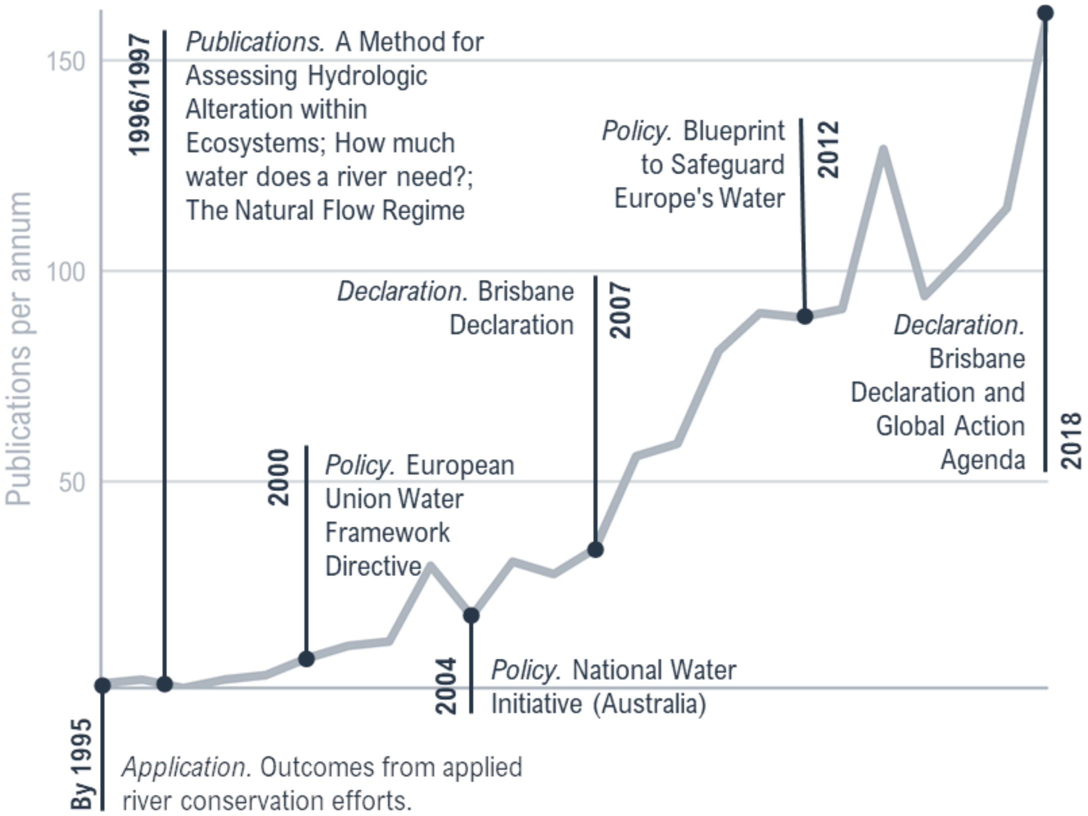

Figure 1-2. Time series of the number of publications (per annum) discussing environmental flows[1]. A timeline of key milestones in the advancement of the environmental flow movement are overlain. *Source: Annie Visser-Quinn*.

Developed during the 1960s and 70s, the first environmental flow methods took a reductionist approach (Poff and Matthews, 2013). In the UK, the 1963 *Water Resources Act* required the determination of a *"minimum acceptable flow"* (c. 38 p. 3 s. 19); further advancement was prohibited by hydrological data limitations (Neachell and Petts, 2017).

It was during the 1990s that the modern environmental flow movement got underway (Figure 1-2). There was increasing recognition of the dynamic nature of the flow regime: the structure and functioning of the riverine ecosystem and adaptation of biota is

[1] Based on a Scopus search on 29-12-2019 with the search terms *{"environmental flows"} OR {"e-flows"} OR {"eflows"}*. Results were manually filtered to remove publications from other fields, including *fluid dynamics* and *hurricane modelling*. A total of 1255 publications were returned, for the period 1995 to 2018.

determined by flow variability. Applied river conservation, such as Arthington *et al.* (1992) in Australia and King and Tharme (1994) in South Africa, provided the empirical evidence necessary to support the provision of a variable flow regime (Poff and Matthews, 2013). The ethos of this body of work was captured in two foundational publications:

- *The Natural Flow Regime.* Poff *et al.* (1997) introduced the concept of the natural flow regime, establishing that *"the integrity of flowing water systems depends on their natural dynamic character"* (p. 769). The dynamic nature of the flow regime is described as central to the maintenance of ecological integrity, either directly, or indirectly through other primary regulators; for example, water temperature, habitat diversity and geomorphology. Poff *et al*. (1997) defined five facets of the flow regime which characterise the range of flows and hydrological events that are critical for the ecological functioning of the river ecosystem. These characteristics are extremely important to the biota that have evolved to thrive therein. A brief introduction to these facets is provided in Table 1-1 alongside examples of their ecological relevance.
- *How much water does a river need?* Richter *et al*. (1996; 1997) introduced the range of variability approach (RVA). The RVA allowed for the comparison of pre- and post-impact conditions (using observed or simulated data), making it possible to quantify the impact of alteration. The ecologically relevant characteristics of the flow regime were captured through a suite of 32 hydrological indices known as the indicators of hydrologic alteration (IHA). The number of indices was limited to minimise redundancy and reduce computational requirements. To date, over 200 ecologically relevant hydrologic indices (ER HIs) have been proposed (Olden and Poff, 2003; Monk *et al.*, 2006; Thompson *et al.*, 2013); redundancy may be reduced through application of statistical techniques such as Principal Component Analysis. See *Appendix A*, Table A-4 for the 84 ER HIs considered in this thesis.

Table 1-1. Facets of the flow regime and examples of their ecological significance. Adapted from Arthington (2012) and references therein.

Facet	Example of ecological relevance
Magnitude. Measure of the volume of water per unit time moving past a specific location.	• Normal flows: Maintaining water temperature, dissolved oxygen content and water chemistry; • Low flows and drought: Providing refuge habitat, e.g. pools; • High flows and floods: Flushing and aeration of gravel (prevents siltation).
Duration. The length of time of a flow event.	• Different tolerances to flood and drought provide opportunity for less dominant species to thrive.
Frequency. How often a given flow event occurs over a given time period.	• Species life cycles are adapted to avoid or exploit certain flow magnitudes or events.
Timing. Seasonal or annual time of flow events.	• Provides environmental cues for life-cycle transitions; • Productivity of riparian vegetation increases as a result of floods in the growing season.
Rate of change (or river flashiness). Measure of the rate at which flow changes from one magnitude to another.	• Seasonal (gradual) rates of change regulate species persistence; • Flashy rates of change, e.g. following a storm, can establish a narrow 'window-of-opportunity' for certain species.

It was this characterisation of the flow regime that made it possible to begin to determine the potential impacts of hydrologic alteration in a quantitative manner. Figure 1-2 illustrates the catalytic effect of this paradigm shift in the quantity of environmental flows research undertaken (Poff and Matthews, 2013).

In the following years, environmental flows were considered in the development of high-level policies such as the European Union *Water Framework Directive* (2000) and Australia's *National Water Initiative* (Council of Australian Governments, 2004). Concerns over the lack of progress towards the goals of the *Water Framework Directive* saw the introduction of the *Blueprint to Safeguard Europe's Water* in 2012 (European Comission). This appears to have led to a refocussed research agenda, with many of the subsequent publications explicitly referring to the blueprint.

By *"setting a common vision and direction for environmental flows internationally"* (Arthington *et al.*, 2018, p. 1), the 2007 Brisbane Declaration has been pivotal in advancing environmental flows research in recent years (Poff and Matthews, 2013; Arthington *et al.*, 2018). The momentous impact the Brisbane Declaration had in advancing the environmental flow movement is made clear in Figure 1-2. The 2018 Brisbane Declaration (Arthington *et al.*, 2018) has seen the reframing of environmental flows in order to recognise new and emerging challenges:

"Environmental flows describe the quantity, timing, and quality of freshwater flows and levels necessary to sustain aquatic ecosystems which, in turn, support human cultures, economies, sustainable livelihoods, and well-being".

Notably, the focus has shifted from restoration to one of adaptation to environmental stressors and a more holistic view of the socio-ecological system. Arthington *et al.* (2018) also highlight the pressing need to consider the implications of climate change, stressing that explicit evaluation of alteration of ecologically important (relevant) flow components, such as timing and duration of peak flows, is critical. The 2018 Brisbane Declaration is accompanied by a Global Action Agenda, with actionable recommendations to guide and support implementation.

Implementation of environmental flows has been largely driven by international investment banks, such as the World Bank and the European Investment Bank. These banks establish guidelines linking the theory to the practical, detailing how environmental flow commitments should be determined in reality. Recent examples include *Environmental flows for hydropower projects: Guidance for the private sector in emerging markets* from the World Bank (2018) and *Environmental, Climate and Social Guidelines on Hydropower Development* from the European Investment Bank (2019).

1.4 CLIMATE CHANGE

Climate is a major determinant of hydrological processes, where precipitation, temperature and evaporation represent the dominant drivers (Arthington, 2012; Cisneros *et al.*, 2014). Consequently, changes in climate will invariably lead to alterations of river flow regimes (Rahel and Olden, 2008; Arnell and Gosling, 2016). As early as 1859, it was hypothesised that changes in atmospheric composition could lead to climatic change (Le Treut *et al.*, 2007). In their fifth assessment report (AR5), the Intergovernmental Panel on Climate Change (IPCC) states that the changes in observed global mean surface temperature since the mid-19th century cannot be explained by natural climate variability alone (Stocker *et al.*, 2013). There is a widespread scientific consensus on the actuality of climate change as the result of human activity (Stocker *et al.*, 2013); the consilience of evidence is only increasing (Oreskes, 2018).

Brief consideration will now be given to hydrometeorological change which may be attributed to climate change. In 2017, it was reported that human-induced warming had reached approximately 1 ± 0.2 °C (likelihood of outcome, 66-100% probability) (Mastrandrea *et al.*, 2010) above 1850–1900 ('pre-industrial') levels (Allen *et al.*, 2018); it is worth noting that greater increases have been observed over land. Anthropogenic climate change has been estimated to have doubled the probability of extreme heatwaves (Stott *et al.*, 2004). Little surprise then, when the Potsdam Institute for Climate Impact Research recently issued a statement affirming that Europe's five hottest summers since 1500 (2002, 2003, 2010, 2016 and 2018) have all occurred since the turn of the century (Rahmstorf, 2019). Research investigating change in global average precipitation has, to date, been conflicting. The IPCC's AR5 reports an increase in the mean (1901-2008/2010), with low confidence in the magnitude of this change due to substantial variations among datasets (Hartmann *et al.*, 2013; Gu and Adler, 2015). No such significant trend has been detected from satellite data (1979-2014) (Adler *et al.*, 2017). Increases in total precipitation and evapotranspiration (Cramer *et al.*, 2014; Mao *et al.*, 2015; Zhang *et al.*, 2016) are more evident from satellite observations; it should be noted that these datasets are only able to provide a limited historical temporal record (from 1982). Attribution analysis of weather events provides a somewhat clearer picture (Cramer *et al.*, 2014). Otto *et al.* (2018) estimated a 60% increase in frequency of extreme rainfall events such as

Storm Desmond, which hit the UK in December 2015, bringing record rainfall of almost 350 mm in a 24-hour period. Attribution of hydrological hazards has been more limited; this is, in part, due to a simple lack of long-term flow records (Cisneros *et al.*, 2014), as well as the confounding factors of land use and hydrologic alteration. Both AR5 (Stocker *et al.*, 2013; Cisneros *et al.*, 2014), and the more recent *Special Report: Global Warming of 1.5 ºC* (Hoegh-Guldberg *et al.*, 2018), report low- to medium-confidence in the attribution of changes in flooding and hydrological drought to climate change; confidence is greatest in regions with significant ice coverage and snowmelt. In the UK, Pall *et al.* (2011) was able to positively attribute the 2000 flooding event in England and Wales to anthropogenic climate change. More generally, a number of studies have suggested that changes in flood frequency across the UK and Europe are the result of a changing climate (Stevens *et al.*, 2016; Blöschl *et al.*, 2019).

As reported in IPCC AR5 (Stocker *et al.*, 2013), changes in climatic behaviour, in terms of both mean and variability, are projected well into the 21st century. For the UK, the most recent projections (UKCP18) suggest a greater probability of *"warmer, wetter winters and hotter, drier summers"* (Lowe *et al.*, 2019); ΔT[2] up to +5.8°C, and ΔP[3] -57% in summer & +33% in winter). Intensification of future flood and drought events, in terms of magnitude, duration and frequency, has also been indicated. Using EDgE flow projections (based on RCP 8.5[4], the worst case emissions scenario evaluated), Visser-Quinn *et al.* (2019a) identified hotspots of change across the UK – locations where concurrent increase in mean annual flood and drought events are projected. Consistent with an earlier iteration (Collet *et al.*, 2018), which utilised Future Flows Hydrology (based on the Special Report on Emissions Scenarios A1B medium emissions scenario), hotspots of change were clustered in the northeast of Scotland and southwest of the UK. Critically, Visser-Quinn *et al.* (2019a) found that, at these hotspots, flood and drought events may occur concurrently or successively, thereby reducing recovery time.

[2] Change in temperature.
[3] Change in precipitation.
[4] The emissions scenarios in the fifth generation Coupled Model Intercomparison Project (CMIP5) are known as Representative Concentration Pathway (RCP); RCP 8.5 represents a radiative forcing that stabilises at 8.5 W/m^2 by 2100.

Climate change represents an additional stressor on an already stressed river ecosystem (Figure 1-1). Evidence suggests that climate change will alter the ecologically important aspects of the flow regime. The potential consequences are difficult to understate, as stated in Arthington (2012a),

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“attention to environmental flows and water management must sit at the heart of climate change adaptation because water is the main medium and vehicle for climate change impacts” (p. 318)

– a sentiment expressly echoed by the IPCC in AR5 (Cisneros *et al.*, 2014) as well as the revised Brisbane Declaration (Arthington *et al.*, 2018).

2. STATE-OF-THE-ART

Methods investigating the impact of climate change on hydroecological response have, typically, been qualitative in nature or quantitative with limited scope (Durance and Ormerod, 2007; Schlabing *et al.*, 2014; Arthington *et al.*, 2018). These quantitative studies rarely consider the impact of the altered flow regime, instead focussing on the direct links between climate (temperature) and hydroecological response (for example Durance and Ormerod (2007), Kupisch *et al.* (2012) and Jyväsjärvi *et al.* (2015)). The work of Schlabing *et al.* (2014) on the effect of climate change on Lake Constance (central Europe), is a rare example of a fully quantitative methodology linking hydrological processes to ecological response. A call towards such a quantitative approach is prominent within the Global Action Agenda appending the updated Brisbane Declaration (Arthington *et al.*, 2018); in the context of climate change, such a move is classified as urgent.

If scope for improvement is to be identified, it is first necessary to provide an overview of the current state-of-the-art in the relevant fields (guided by the conceptual framework underlying Schlabing *et al.* (2014)): hydroecological modelling and future flow projections. A necessary spotlight will, further, be thrown on the background of uncertainty. Understanding the inherent limitations will define the gaps in which marked improvements, not only can be made, but should be.

2.1 HYDROECOLOGICAL MODELLING – ECOLOGICAL RESPONSE TO FLOW

Methods for determining environmental flow limits range from simple look-up tables to detailed statistical models (Tharme, 2003; Arthington, 2012d); mechanistic or process-based models remain uncommon due to the complexities inherent to the hydroecological relationship. Herein, the focus is on empirically based multiple linear regression models based on the range of variability approach in Richter *et al.* (1996; 1997). These hydroecological models can be developed at different scales, from the single case study river model with multiple sample sites (Exley, 2006; Visser *et al.*, 2017), to models encompassing a given region or particular flow regime (Monk *et al.*, 2007; Worrall *et al.*, 2014). The method described here has been employed routinely in many studies over the past two decades, for example see Clausen and Biggs (1997), Exley (2006), Monk *et al.* (2006; 2008; 2017), Dunbar *et al.* (2009), Worrall *et al.* (2014) and Bradley *et al.* (2017).

In the past, an assortment of chemical and physical indicators had been in use for the assessment of river health. Despite these efforts, the rate of decline in the health of river ecosystems remained on the rise; consequently, these indicators were deemed insufficient to protect (Norris and Thoms, 1999; Pearson, 1999). Since the 1990s, there has been a shift towards a more holistic approach through the use of biological indicators, representing the functional composition of the instream macroinvertebrate community (Arthington, 2012c). This is due to: sensitivity to environmental change and perturbation; positioning at the intermediate trophic levels of the instream food web; and relative ease & cost-effectiveness of data sampling (Acreman *et al.*, 2008; Holt and Miller, 2010; Hill *et al.*, 2013). Freshwater macroinvertebrates are known to be particularly sensitive to changes in flow regime (Chutter, 1969; Extence *et al.*, 1999; Arthington, 2012c), making them ideal for the assessment of the ecological implications of a changing flow regime (hydrologic alteration). Sampling is typically carried out during the peaks of macroinvertebrate activity in spring (Apr-Jun) and autumn (Oct-Dec) (Lenz, 1997). The Lotic-invertebrate Index for Flow Evaluation (LIFE; Extence *et al.*, 1999), a weighted index which takes into account the flow-velocity preferences of the macroinvertebrate community, is frequently used, and considered herein. Further details are provided in Appendix A.

A suite of ecologically relevant hydrological indicators is determined, representing the five facets of the flow regime (Table 1-1). Capturing both inter- and intra-annual variation (between year and within year flow respectively), the indicators are determined for the period (typically 6-12 months) which immediately precedes the macroinvertebrate sampling. With an excess of 200 available indicators, this is, commonly, followed by the application of statistical approaches such as PCA (Olden and Poff, 2003; Monk *et al.*, 2008).

The structure of hydroecological models are, primarily, derived through stepwise regression, a methodology rendered attractive, in general, by well-established underlying statistical theory and assumptions (Whittingham *et al.*, 2006). An algorithm adds and/or subtracts variables (in this case, hydrological indices) according to identified criteria, stopping once the criterion has been met, resulting in a single, final model. The assumption is that this single model represents the 'best' model with the most predictive power.

The review of the literature reveals two key research gaps. A number of studies (Boulton, 2003; Wood and Armitage, 2004; Wright *et al.*, 2004; Durance and Ormerod, 2007) have observed a delayed community response to antecedent flow conditions (or lag in hydroecological response), particularly in the case of extreme flow disturbances. It has been hypothesised (Bunn and Arthington, 2002; Klaar *et al.*, 2014) that this focus on a single year of antecedent flow may overlook critical information, leading to inaccuracies in the hydroecological modelling. Consequently, it appears critical to consider flow across multiple years, i.e. the cumulative impact. Despite this, limited work has been carried out to directly explore the effects of this lag on the hydroecological relationship. With projections of increased climate variability and more frequent extreme events (Wilby *et al.*, 2010; Prudhomme *et al.*, 2014; Chadd *et al.*, 2017), the need to consider this lag in hydroecological response cannot be understated.

The limitations of stepwise methods are increasingly recognised and acknowledged (Whittingham *et al.*, 2006; Wasserstein and Lazar, 2016), but not, it appears within hydroecological modelling, where the use of stepwise methods remains the norm. These limitations include the misinterpretation of p-values and a focus on a single best approximating model, resulting in an incomplete representation of model uncertainty. The concern is that, as further aspects of the hydroecological relationship are understood, such as lag in ecological response (which reduces already limited data availability), the likelihood of model uncertainty may increase, unaddressed.

2.2 FUTURE FLOW PROJECTIONS

Hydrological models serve to bridge the gap between global climate change projections and the need to understand the impact of climate change at a more localised scale (Gleick, 1986). Here, hydrological models are first discussed, followed by a brief introduction as to their application in climate impact studies.

The river catchment represents a hydrologic system. Capturing the full detail of this system is impractical due to its complex nature. Therefore, an abstraction of the system is necessary. This simplification is achieved using hydrological models; precipitation and streamflow serving as the primary input and output respectively. Hydrological models are essentially mathematical models that represent the system behaviour through a set of equations and logical statements (Chow *et al.*, 1988). They are conceptual in nature, being based on a combination of prior knowledge of the physical characteristics of the catchment, combined with empirical data. The lumped model, the most simplistic representation, considers the basin as a homogeneous whole. The semi-distributed model determines the flow contributions from separate areas, or sub-catchments, which are in themselves considered to be homogeneous. With the fully distributed model the catchment is subdivided into much finer grid units or a mesh from which the relative flow contributions are determined.

In his primer on rainfall-runoff modelling, Beven (2012) states that the focus within hydrological modelling is model selection, followed by the parameterisation and evaluation of the selected model structure(s). The aim of this parameterisation exercise is to determine the values of model parameters which achieve the best level of agreement between the observations and simulated outputs. A myriad of parameterisation approaches are available. Examples include: the traditional algorithmic approach which makes use of objective functions and performance measures; approaches based on the flow duration curve such as Westerberg *et al.* (2011); and the covariance approach (Vogel and Sankarasubramanian, 2003).

Note that parameterisation and evaluation are more commonly referred to as calibration and validation. In this thesis, the terms parameterisation and evaluation are used for philosophical reasons; see *Glossary of terms* on page xi for further details.

Research into the hydrological impact of climate change has been ongoing for over two decades (Olsson *et al.*, 2016). Thousands of peer-reviewed articles have been published on the subject[5]. Whilst a number of different approaches are possible, Olsson *et al.* (2016) describe the underlying conceptual framework as a top down approach, where projections from climate models (Generalised Circulation Models or Earth System Models) are used to drive (parameterised) hydrological models for the basin or region in question. A range of scenarios, storylines and pathways of greenhouse gas concentrations may be considered; thus, a variety of responses to climate change can be modelled.

2.3 REPLICATION OF ECOLOGICALLY RELEVANT HYDROLOGICAL INDICATORS

Environmental flows research makes use of hydrological models to explore the impact of hydrologic alteration. Methods exploring this alteration are based on the RVA and IHA approaches introduced previously (*1.3 Environmental flows*); examples include the ecological limits of hydrologic alteration (Poff *et al.*, 2010). To recap, hydrological models are parameterised and run for pre- and post-impact conditions; model simulated indicators may subsequently be derived and compared. This approach differs from hydrological modelling as described above, as the focus is on replicating specific hydrologic processes as opposed to the hydrograph (time series). Shrestha *et al*. (2016) report that recent studies following these methods have been subject to significant errors. They surmise that at present, hydrological models are unreliable in their replication of hydrologic indicators and that users should exercise caution in using them. There are, thus, concerns surrounding the present validity of future projections of ER HIs.

[5] Based on a Scopus search on 23-12-2019 with the search terms *"rainfall-runoff model" OR "hydrological model") AND "climate change"*. A total of 2470 publications were returned, beginning in 1988.

2.4 UNCERTAINTY

Flow projections are the output from a long and complex modelling chain (Clark *et al.*, 2016). With each (modelling) step, uncertainty cascades, propagating (or constraining) the uncertainty through the modelling chain (Warmink *et al.*, 2010; Clark *et al.*, 2016). These uncertainties can arise form a number of sources. In climate modelling, the sources include, but are not limited to (Clark *et al.*, 2016):

- *Epistemic uncertainty.* Despite significant advancement over time (Edwards, 2011), there remains a great deal of epistemic uncertainty: uncertainty either due to a lack of knowledge, or an ability to capture the requisite processes, within climate modelling. For example, it is not currently possible to simulate the physical processes relating to cloud formation (Frigg *et al.*, 2015b).
- *Scenario uncertainty.* The future trajectory of climate remains unclear. Thus, it is necessary to consider multiple emissions scenarios, leading to a wide range of projections.
- *Internal climate variability.* The natural, unforced climate variability is the result of atmospheric, oceanic, terrestrial and cryospheric processes and interactions (Kay *et al.*, 2014). Model error and internal climate variability are often difficult to disentangle due to the insufficient length of observed data. The associated uncertainty can be greater than scenario uncertainty (Wilby, 2005; Kay *et al.*, 2014).
- *Structural uncertainty.* A reflection of the lack of knowledge about the physical mechanisms. Models differ in the components included (e.g. aerosols, stratospheric chemistry) and how these are represented.
- *Parameter uncertainty and equifinality.* Uncertainty in the values of climate model parameters. Climate models feature a large number of variable parameters, many of which cannot be observed. Equifinality, the presence of multiple best fit parameter sets, is a further complication.
- *Tailoring or downscaling uncertainty.* The tailoring of climate projections prior to use through downscaling and bias correction (Olsson *et al.*, 2016). Indeed, the uncertainty which may be introduced through downscaling methods has seen the birth of a whole new field of research.

All of these uncertainties propagate within the impact model, in this case the hydroecological model. Further, there are additional, and significant, uncertainties associated with hydrological modelling. Visser-Quinn *et al.* (2019a) have shown that these uncertainties may even be greater than the uncertainty associated with the climate projections. Many of the sources of uncertainty in hydrological modelling are also found in climate modelling, for instance, inadequate representation of the underlying processes, structural & parametric uncertainty and equifinality.

Clark *et al.* (2016) discuss the characterisation and minimisation of the uncertainty associated with the hydrological impacts of climate change. The authors state that research into the impact of climate change on hydrology has hitherto *"neglected or underestimated many of the[se] uncertainties".* Clark *et al.* go on to say that the tendency in hydroclimatological studies has been to focus on one aspect, or source of uncertainty, at the expense of others. Much of this focus has been directed towards climate models, and less so on the hydrological models and the propagation of uncertainty. The authors recommend a move away from the current ad hoc approach to uncertainty, to a more focussed and holistic depiction of uncertainty. The characterisation and minimisation of all sources of uncertainty in the modelling chain is deemed essential going forwards.

Presently, substantial uncertainty associated with hydrological projections represents a key challenge to practical application (Clark *et al.*, 2016). It also raises questions about the validity of using these flow projections for further impact assessment, such as the hydroecological impact.

3. PROBLEM STATEMENT

A lag in hydroecological response has been observed across a number of studies. With projections of increase flow variability, this raises concern over the impact of climate change. Capturing this complexity is a necessary driving force to the work contained in this thesis. Given the backdrop of uncertainty, the robustness of the current stepwise approach to hydroecological modelling is thus called into question. Distinct from this, the suitability of traditional hydrological modelling practices in replicating ER HIs is also in question. Finally, a review of uncertainty revealed that the current approach to hydroclimatological modelling is subject to significant unknowns and uncertainties which, often, remain unacknowledged.

4. RESEARCH QUESTIONS AND OBJECTIVES

This work seeks to facilitate a better understanding of long-term hydroecological relationships and ecological response to changes in flow variability, changes which would undoubtedly occur under climate change. Given the complexity inherent to ecology, hydrology, and climate change projections, eliciting the possible hydroecological implications with any degree of confidence is highly challenging. The central objective of this research is a clear reflection of the project title, *Understanding riverine hydroecological response to climate change: Development of a coupled modelling framework*. Figure 1-3 outlines the conceptual framework through which this may be achieved. A hydrological model forced with climate change projections may be used to simulate the changes in the flow regime (in the form of ER HIs). These projections serve as input to a hydroecological model, providing projections of ecological response under climate change. With inadequate representation of uncertainty in modelling leading to suboptimal decision-making, there is a clear focus on the characterisation and minimisation of uncertainty throughout.

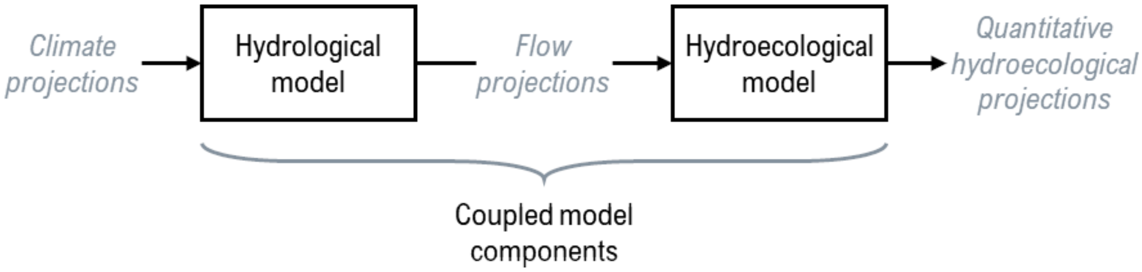

Figure 1-3. Conceptual framework through which the central objective of this thesis may be achieved. *Source: Annie Visser-Quinn.*

This PhD thesis follows a prospective model, where a series of publications, forming the main body of the work, are designed to answer the research questions. Each research question is guided by a series of secondary objectives. Figure 1-4 details how elements of the methodological framework map to these research questions and objectives. The wider applicability of the coupled modelling framework and the component models is explored via one principal, and four additional, case studies; details are provided in the following chapter.

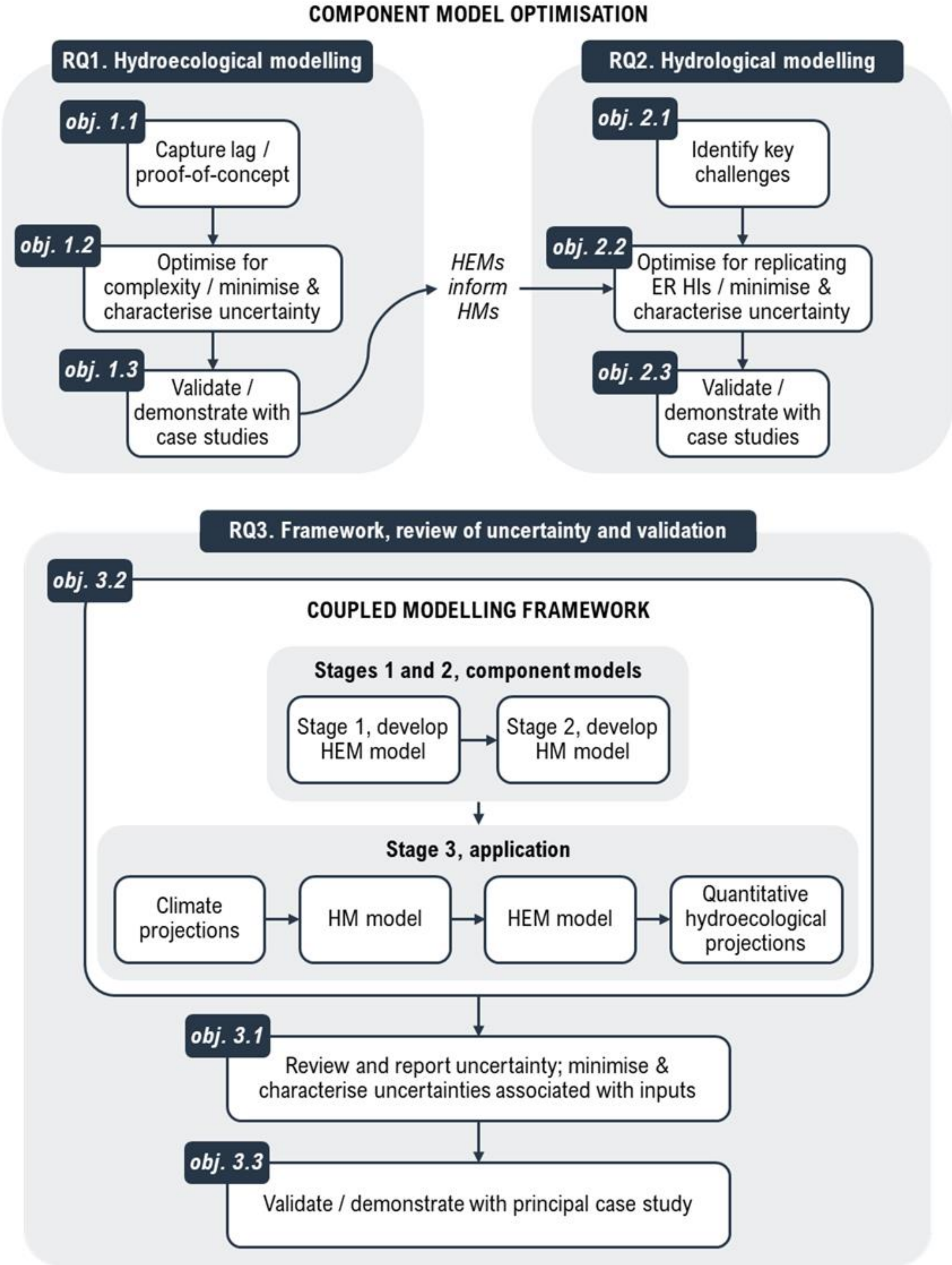

Figure 1-4. Outline of the methodological framework underlying this thesis; labels indicate how each element maps to the research questions and objectives. Note the consideration of uncertainty throughout. Abbreviations are defined as follows: ER HIs, ecologically relevant hydrological indicators; HEM, hydroecological model; and HM, hydrological model. *Source: Annie Visser-Quinn.*

4.1 RESEARCH QUESTION 1

The use of numerical models that link flow regime and freshwater ecological response is well-established. In this first research question, the aim is to use numerical models to develop current understanding and modelling of this hydroecological relationship through consideration of potential delays in hydroecological response. Objective 1.1 serves as a proof of concept to determine whether lag in ecological response may be accounted for by the hydroecological model. This is achieved through the incorporation of time-offset hydrological indicators. With this increased complexity, objective 1.2 considers the statistical robustness of the traditional hydroecological modelling approach against an information theory multi-model approach. Objectives 1.1 and 1.2 focus on the principal case study only, the wider applicability of the derived methodology is the focus of objective 1.3.

1) **Can hydroecological models account for a potential delay in hydroecological response?**
   1.1. To incorporate time-offset hydrological indicators in a hydroecological model as ‘proof of concept’.
   1.2. To determine a statistically robust methodology capable of capturing the increased complexity (objective 1.1).
   1.3. To validate and demonstrate the application of the derived methodology (objective 1.2) across a range of case studies.

4.2 RESEARCH QUESTION 2

The second research question looks to determine whether hydrological models can preserve ecologically relevant characteristics of the flow regime. The first stage of work (objective 2.1) requires developing an understanding of the known limiting factors through a review of the literature. These findings thus inform the determination of a more robust hydrological modelling approach under objective 2.2. Again, the wider applicability of the method is demonstrated through application across a range of case studies (objective 2.3).

2) **Can hydrological modelling be optimised towards the preservation of ecologically relevant characteristics of the flow regime?**
    2.1. To identify the key challenges inherent to the preservation of these characteristics.
    2.2. To determine a robust hydrological modelling approach in support of the preservation of the characteristics identified in objective 2.1.
    2.3. To validate and demonstrate the application of the derived methodology (objective 2.2) across a range of hydrologically diverse case studies.

4.3 RESEARCH QUESTION 3

The characterisation and minimisation of uncertainty is central to the development of the coupled modelling framework. Objective 3.1 facilitates a review of the uncertainties introduced by the component models, as well as a discussion of uncertainties associated with model inputs. The coupled modelling framework is then formed (objective 3.2) as the sum of the outcomes from each of the previous objectives. The development of a hydroecological model and parameterisation of a hydrological model represent stages 1 and 2 of the coupled modelling framework respectively (Figure 1-4). In stage 3 of the framework, climate projections serve as the input to the coupled model, providing the quantitative hydroecological projections of climate change impacts. The ability of the coupled framework is illustrated through application to the principal case study (objective 3.3).

3) **Can climate change projections be used in the determination of quantitative hydroecological outcomes?**
    3.1. To characterise and minimise the uncertainty introduced to the coupled modelling framework.
    3.2. To determine a coupled modelling framework to assess the hydroecological impact of climate change.
    3.3. To validate and demonstrate the coupled modelling framework for the principal case study, the River Nar.

5. THESIS STRUCTURE

The following chapter provides an overview of the principal and additional case studies. The subsequent three chapters of this thesis are structured around the three stages of the framework detailed in Figure 1-4, with each of the three research questions mapping to a stage. Following a prospective model, the main body of work is presented through publications, with accompanying foreword and afterword for context.

Chapter 3 – Hydroecological modelling sees the development of the methodology which forms stage 1 of the coupled modelling framework. Here, delays in hydroecological response to perturbation are incorporated into the hydroecological modelling through the addition of time-offset hydrological indicators. The derivation of an improved more robust hydroecological modelling approach follows. These matters are resolved through two publications in the journal *River Research and Applications*. The methodology is subsequently validated through application to the five case study catchments.

The second stage of the framework is the focus of *Chapter 4 – Hydrological modelling*. Here, the focus is on optimising hydrological models for the replication of ecologically relevant characteristics of the flow regime. The chapter opens with a review of the literature, identifying the key challenges inherent to the preservation of these characteristics. In answer, the third publication presents a modification of Vogel and Sankarasubramanian's (2003) covariance approach; validation is achieved through application to the five case studies. The afterword reviews the relative success of this approach (relative to four recent studies).

In *Chapter 5 – Coupled modelling framework*, the work from the previous two chapters is brought together to form the coupled modelling framework. The characterisation, and minimisation, of uncertainty are central to the framework development; accordingly, the chapter opens with a summary of the treatment of uncertainty within the framework. The remainder of the chapter centres around the fourth and final publication, which details the framework in its entirety alongside validation through application to the principal case study. The benefits of the framework are briefly considered in this publication but revisited in more detail in chapter 6.

A discussion chapter follows, providing first an overview of the outcomes and relevance of each research question, with a particular focus on research question 3 and the coupled framework. The limitations section explores the obstacles facing the practical implementation of the framework: inertia, ecological data availability and the associated workload. This is followed by a review of the implications of the assumption of non-stationarity which underpins the majority of climate change impact modelling. The chapter closes with consideration of the scope for further research, principally informed by the current trajectory of research.

Chapter 7 – Conclusions brings this thesis to a close. There are two appendices. Appendix A includes ancillary information relating to the hydroecological modelling: the method for determining the Lotic-invertebrate Index for Flow Evaluation (LIFE) score, the full suite of ecologically relevant hydrological indicators considered as well as the hydroecological model structures derived at the close of Chapter 3. Appendix B features a final supplementary publication.

CHAPTER 2. CASE STUDY CATCHMENTS

This chapter introduces the case studies and their reasons for selection. The coupled modelling framework is developed via the principal case study, the River Nar, a groundwater-fed chalk river in Norfolk, southeast England. The rationale for the selection of the River Nar was manifold:

(1) The river has been subject to continuing research into its flow regime, and their governing factors (Sear *et al*., 2005; Visser, 2014; Garbe *et al*., 2016; Garbe and Beevers, 2017);

(2) The length of the available hydrometeorological (50+ years) and hydroecological (20+ years) time series;

(3) Delays in ecological response have been previously observed (Visser, 2014); this is considered further in the course of Chapter 3 – Hydroecological modelling.

In the pursuit of research questions 1 and 2, the development and validation of the component model methodologies, four hydrologically diverse case studies are also considered. The selected catchments are located across the UK (Figure 2-1), from the northeast of Scotland near Aberdeen, to the southwest of England on the boundary of Dartmoor National Park.

The first section of this chapter provides an overview of the principal case study, the River Nar. This is followed by discussion of the three key considerations in the selection of the additional case studies: ecological & hydrological data availability and hydrological diversity. A profile of each selected case study is presented with respect to these criteria. It is important to keep in mind that these catchments are purely the vector by which the analysis is performed; the individual outcomes are incidental.

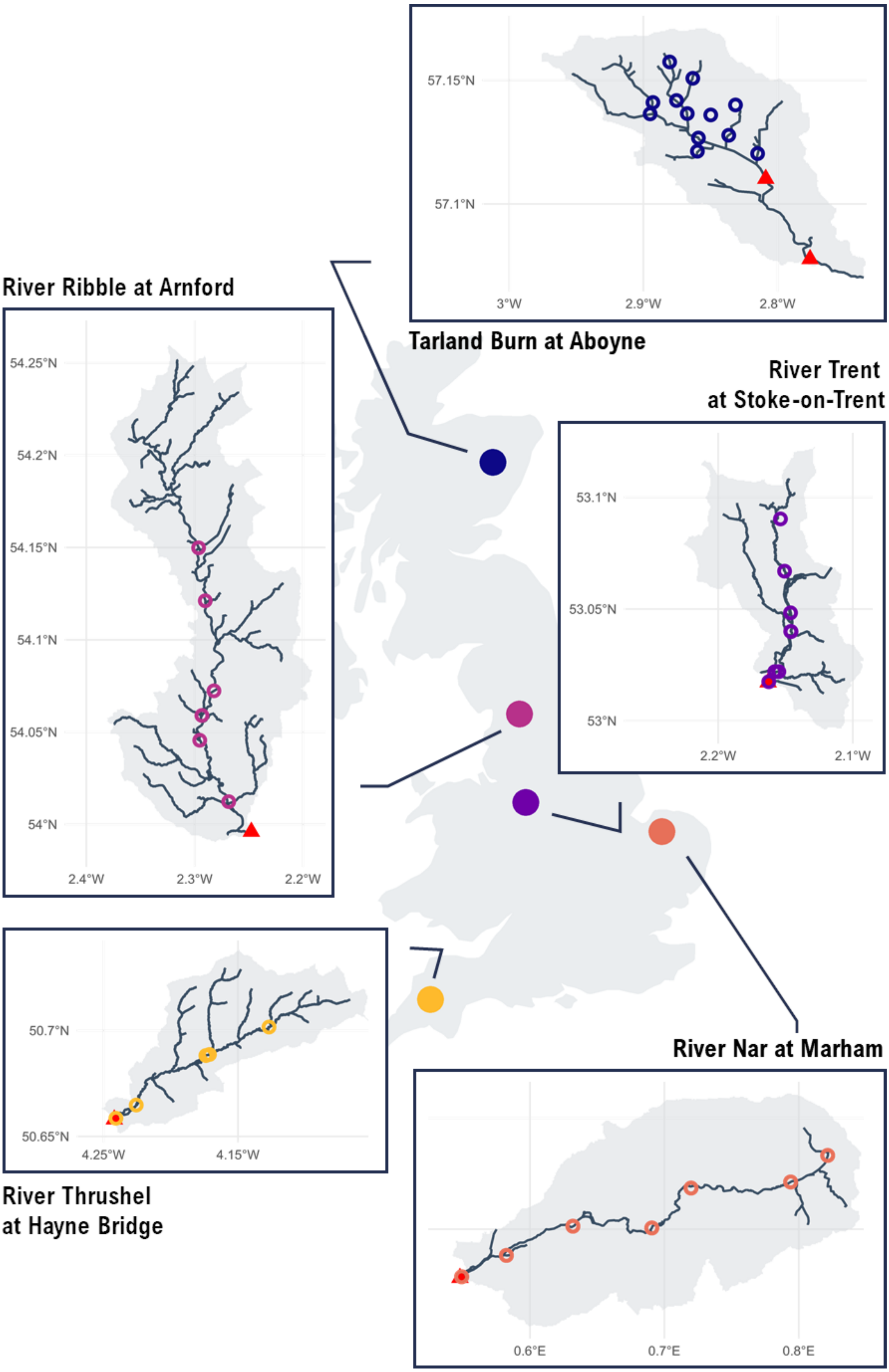

Figure 2-1. Locations of the five case study catchments. Inset: Catchment outlines with ecological monitoring sites (hollow circles) and flow gauges (red triangles) indicated. *Data source: rnrfa package (Vitolo et al., 2016, 2018). Source: Annie Visser-Quinn.*

1. PRINCIPAL CASE STUDY: RIVER NAR

The River Nar is a chalk stream located in Norfolk, south-east England (Figure 2-1). The upper Nar overlies a chalk scarp to Marham, the river's midpoint, whilst the lower alluvial reach forms a fen basin. With these two distinct river units, the River Nar has been designated a Site of Special Scientific Interest (Bertholdt, 2018). Flow is gauged at the river's midpoint; thus, the focus is on the 153.3 km^2 upper catchment (chalk reach) (as shown in Figure 2-1).

1.1 CATCHMENT FORMATION

The chalk sub-catchment is primarily made up of a cretaceous chalk cuesta (Sear *et al*., 2005). The wider catchment landscape is principally the result of two major glacial periods: the Anglian glaciation (480-430 kBP, 1,000 years before present), which created the fen basin, followed by significant glacial remodelling during the Wolstonian glaciation (300-130 kBP). The formation of the fen basin, and resultant dissection of the chalk, created two distinct river units, marked by a significant gradient change at Narborough. The chalk sub-catchment is the steepest, featuring 90% of the topographic range and a mean gradient of 0.0020. Beginning in 5000 BP, forest clearance saw the mobilisation of large volumes of fine sediments. Over time these sediments blocked the innumerable river channels, prevented channel shift, producing one single meandering river.

1.2 HYDROLOGY

The River Nar is predominantly a groundwater-fed river with a BFI of 0.91. Flow is primarily sustained by springs. Upstream reaches are maintained by groundwater seepage & surface water runoff and are particularly vulnerable to low flows (Sear *et al*., 2005).

With a highly seasonal flow regime (Figure 2-2), the hydrology of the River Nar is characteristic of pure chalk streams (Sear *et al.*, 2005); aquifer recharge occurs in the autumn months, with a progressive rise in flow until March/April. Flow is relatively low (Figure 2-2), over the available 1953-2018 record, the median flow is 0.94 m^3/s, whilst Q10 and Q90 flows are 2.02 and 0.49 m^3/s respectively; where Q10 and Q90 represent the 10% and 90% flow exceedance respectively (equivalent to 90^{th} and 10^{th} percentiles). As of

September 2018 (the most recent data currently available), the year 1991 saw the longest hydrological drought on record (Garbe *et al.*, 2016), with flow falling below Q95 for 178 consecutive days.

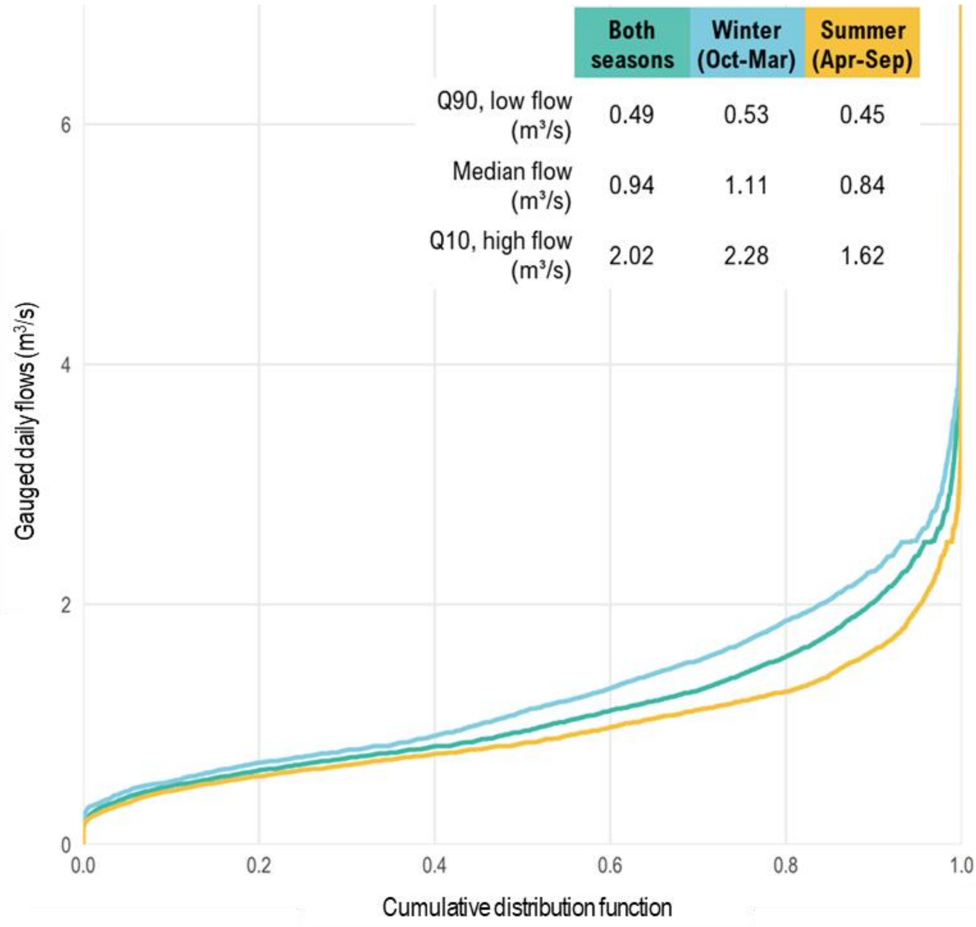

Figure 2-2. Flow distribution curve (a cumulative distribution function) of the gauged daily flow at the Marham gauge, River Nar, for the period 1953-10-01 to 2018-09-30. *Data source: rnrfa package (Vitolo et al., 2016, 2018). Source: Annie Visser-Quinn.*

1.1 HYDROMORPHOLOGICAL PRESSURES

Hydromorphological pressures are stresses which come as a direct result of changes in river hydromorphology, the shape and structure of the water course. Historically, the River Nar has suffered from significant hydromorphologic pressures, with a long legacy of channel modifications along 90% of its length (Norfolk Rivers Trust, 2014). The majority of the channel modifications derive from navigation, possibly as early as the 12th century, and extend upstream as far as Castle Acre, the midpoint of the chalk reach. Other historical modifications include ornamental estate lakes, water meadows and water mills. The 20th century agricultural drainage programme is considered most damaging due to the scale and intensity of the changes (Norfolk Rivers Trust, 2014). The already fragile state of the river is further exacerbated by modern pressures: land use (sediment and nutrient pollution) and over-abstraction. The main source of sediments is catchment, with over 75% arable land use. These fine sediments clog the characteristic chalk gravel beds, thereby inhibiting ecosystem functionality. Groundwater and surface water are classified as over-licenced and over-abstracted respectively. There are particular concerns about the impact of abstraction in drought years (Norfolk Rivers Trust, 2014). Given the extent of the historical modifications, continuing modern pressures, and gentle pace of the river, there are significant concerns over resilience of the River Nar to future pressures of climate change and population growth.

2. CASE STUDIES OVERVIEW

2.1 ECOLOGICAL & HYDROLOGICAL DATA AVAILABILITY

The co-location of ecological and hydrological monitoring sites is necessary to enable the development of hydroecological models. Additionally, the sites are required to have sufficient hydrological and climatological data for the derivation of the hydrological models.

Three locations (River Trent, River Ribble, and the River Thrushel; Figure 2-1) were identified through mapping biotic data from the Environment Agency's *Freshwater and Marine Biological Survey for Invertebrates England* (known as BIOSYS) (Environment Agency, 2018) to National River Flow Archive (NRFA) catchments with daily gauged flow (Vitolo *et al.*, 2016, 2018); this hydrological data was then paired with climate data (precipitation and temperature) (Met Office, 2018b, 2018a). To ensure wide spatial coverage, and consideration of the role of peat on catchment dynamics, the Tarland Burn in Scotland was also selected; the hydrological and ecological data was provided by the James Hutton Institute, Scotland. For the River Nar, raw macroinvertebrate data identified to species level was directly provided by the Environment Agency, on licence.

A summary of the data availability for each case study is provided in Table 2-1; catchment outlines and the locations of the hydroecological monitoring sites are detailed in Figure 2-1 previously. The availability of ecological and hydroclimatic data is variable and should serve to highlight the applicability of the component models for realistic cases. The specific data utilised is detailed in each chapter / publication.

Table 2-1. Case study summaries in terms of catchment characteristics and ecological & hydroclimatological data availability. The span of years is specified, with the number of years with data provided in brackets. For case study locations, catchment outlines and sampling locations, see Figure 2-1. *Data source: rnrfa package (Vitolo et al., 2016, 2018).*

		Tarland Burn	**River Trent**	**River Ribble**	**River Nar**	**River Thrushel**
Catchment characteristics	*Area (km²)*	70.9	53.2	204	153	57.6
	Baseflow index	0.66	0.44	0.25	0.91	0.39
Ecological data	*Season*	Summer (Jul-Sep)	Spring (Apr-Jun)			
	Years (discrete)	2000-2007 (7)	1992-2018 (17)	1995-2015 (9)	1986-2014 (25)	1990-2007 (11)
	No. monitoring sites	12	9	6	7	6
	No. data points	81	45	14	106	27
Hydro-climatological data	*Years (continuous)*	2003-2016 (13)	1989-2016 (27)	2000-2016 (16)	1961-2015 (54)	1989-2016 (27)

2.2 HYDROLOGICAL DIVERSITY

The principal case study has a BFI of 0.91. To confirm the hypothesis of delays in hydroecological response it is necessary to consider a range of catchments with different groundwater contributions. From Figure 2-3a it can be seen that the five case studies capture the full range of BFI observed in the UK.

Related to the above, the catchment geology and level of permeability provide an insight into catchment hydrological processes. The case studies reflect the full range of bedrock permeability, as defined by the NRFA. The Tarland Burn does not feature in the NRFA; therefore, the parent catchment is presented in Figure 2-3b; covering only 9% of the parent catchment area, these numbers are subject to uncertainty.

Figure 2-3c depicts catchment land cover, based on the Centre for Ecology & Hydrology's 2007 Land Cover Map (Centre for Ecology and Hydrology, 2011). Land cover provides insights into the hydrological processes on the catchment surface. Diversity across the catchments is clear. Land cover is predominantly arable, horticulture and grassland. The River Trent features the largest urban area (Stoke-on-Trent); there were no other catchments with significant urban land cover with sufficient ecological data availability. Land cover in the Tarland Burn is predominantly heath and bog; in the figure, as above, the parent catchment serves as a proxy.

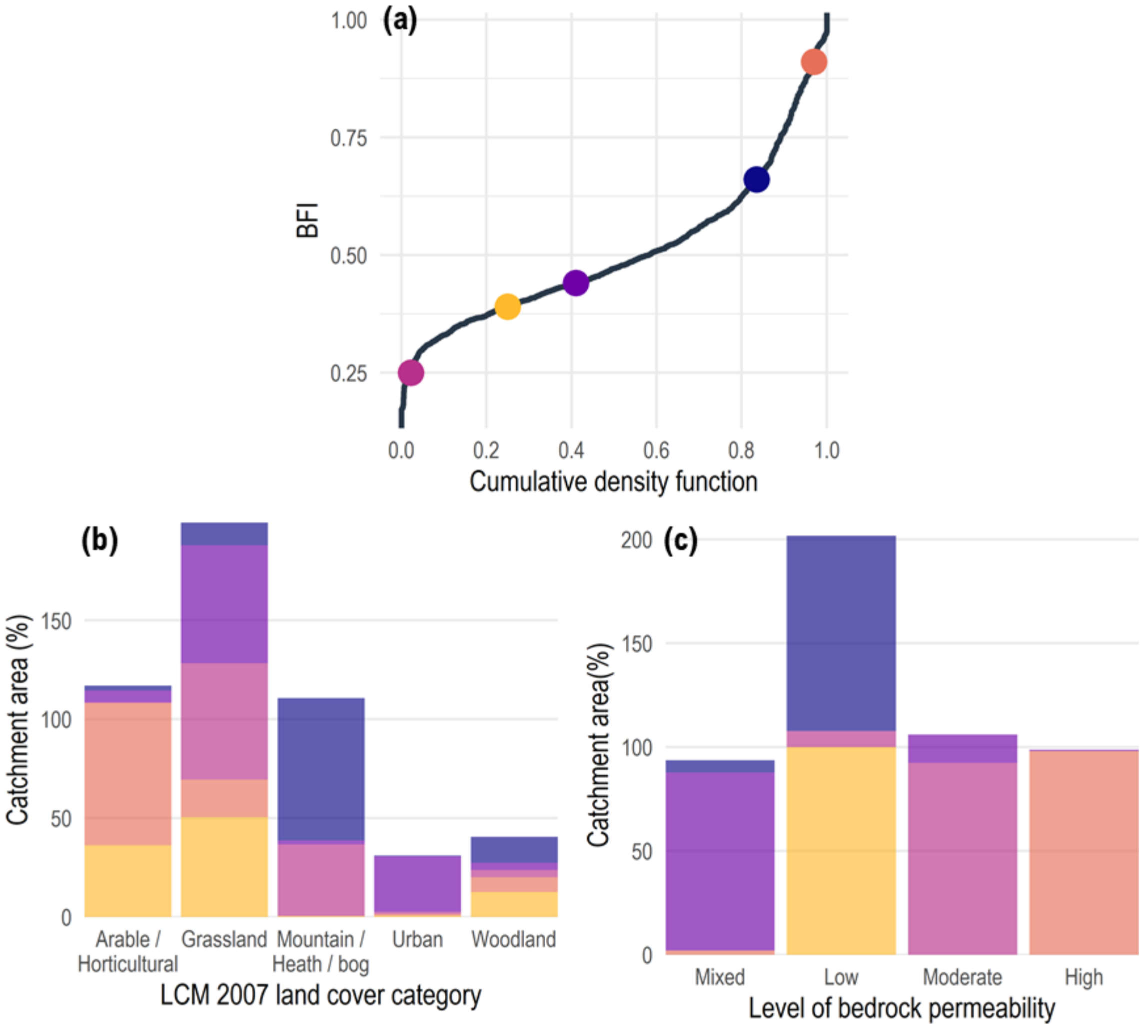

Figure 2-3. Compound figure of case study catchment characteristics. *(a)* Case study location BFI overlaying BFI of all NRFA catchments. *(b)* Land cover as a percentage of catchment area*; from the Centre of Ecology & Hydrology Land Cover Map (LCM) 2007.

(c) Permeability of bedrock geology as a percentage of catchment area*. *Data source: rnrfa package (Vitolo et al., 2016, 2018). Source: Annie Visser-Quinn.*
* Note, in (b) and (c), the Tarland Burn parent catchment, 12001, is used as a proxy.

Additional insights as to the hydrological diversity of the selected catchments may be gained through Figure 2-4; flows are standardised by catchment area to facilitate comparison. Across the five catchments, the average day of minimum flow ranges over two months, from early July to early September. The maximum flow counterpart has a 50-day range from late December to mid-February. In both cases, timing in the River Nar is later than the four additional catchments.

A review of the average (median) flow magnitude follows:

- *Tarland Burn.* Flow magnitude is low but stable over the summer months (Jun-Oct). The remainder of the year is subject to much greater variability. The flow on the average day of maximum flow is approximately 6 times greater than the minimum;
- *River Trent.* Again, flow is relatively stable in summer, with increasing variability in winter. The flow on the average day of maximum flow is slightly below the River Trent, at approximately 4.9 times greater;
- *River Ribble.* There is high flow variability from summer to winter. On average, winter peak flow is 14 times greater than the summer minimum;
- *River Nar.* Being groundwater-fed, the time series is both smooth and sustained through the year; variation across the interquartile range is much less compared to the other catchments. The flow ratio for the average day of minimum and maximum flows is low at 2.9;
- *River Thrushel.* The flow on the average day of minimum flow is extremely low at 0.1 mm/day. Indeed, these extremely low flows occur for at least four months of the year (May-Sep), flow then rises from October to December. Of the case studies, the River Thrushel has the largest range in flow under average conditions.

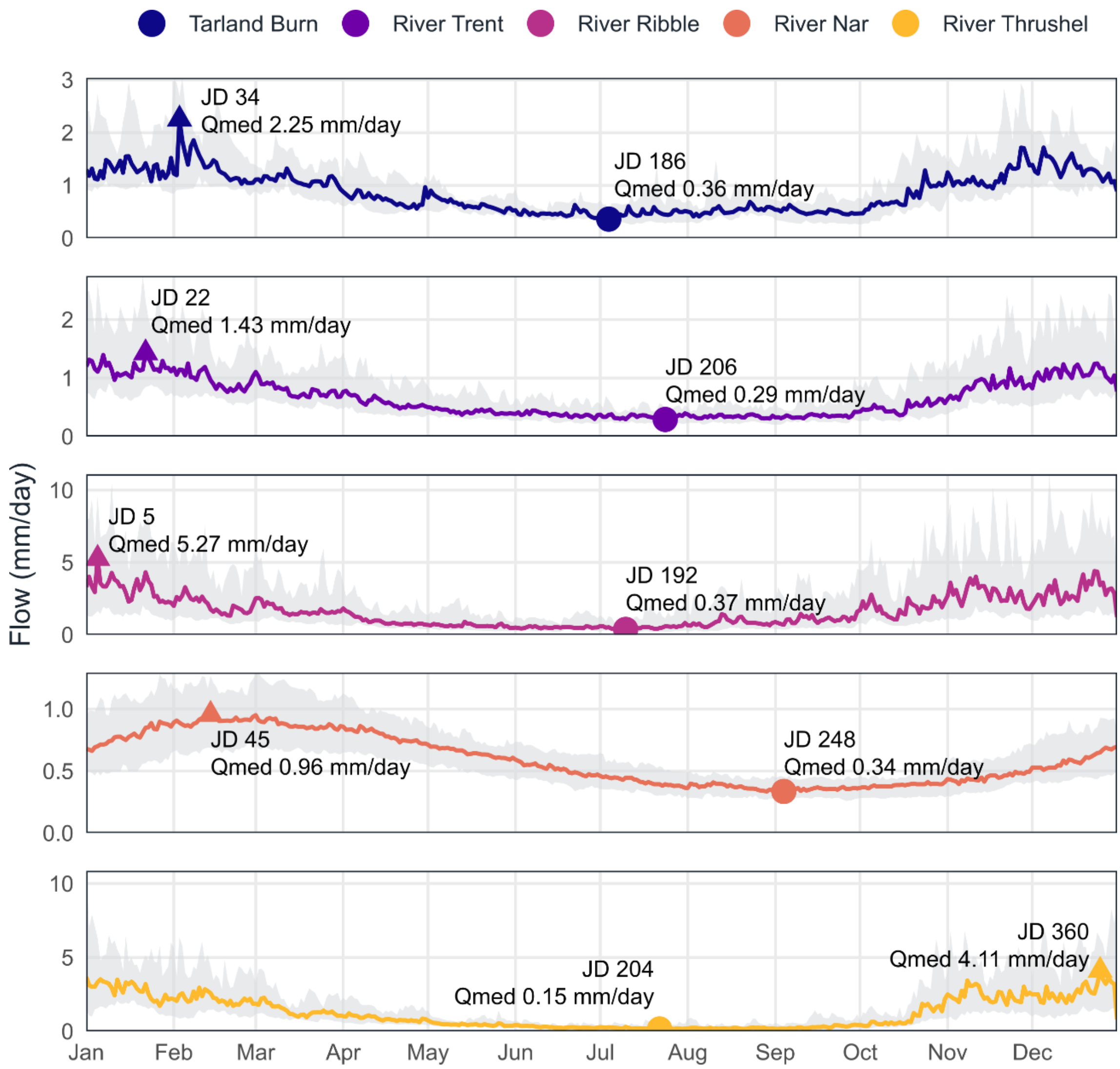

Figure 2-4. Time-series of the median daily flow, overlying the daily interquartile range. The average (median) day of minimum and maximum flow are marked. *Data source: rnrfa package (Vitolo et al., 2016, 2018). Source: Annie Visser-Quinn.*

CHAPTER 3. HYDROECOLOGICAL MODELLING

In its most basic form, the hydroecological relationship represents the link between hydrology and ecology. The focus of this chapter is on improving the current understanding and representation of this relationship, specifically with regards to the delayed response phenomena. The main outcome is an uptodate hydroecological modelling approach which forms stage 1 of the coupled modelling framework (Figure 1-4). This chapter, then, maps to research question 1 and is guided by three research objectives:

1) **Can hydroecological models account for a potential delay in hydroecological response?**
    1.1. To incorporate time-offset hydrological indicators in a hydroecological model as ‘proof of concept’.
    1.2. To determine a statistically robust methodology capable of capturing the increased complexity (objective 1.1).
    1.3. To validate and demonstrate the application of the derived methodology (objective 1.2) across a range of case studies.

Objectives 1.1 and 1.2 are satisfied through two publications in the academic journal *River Research and Applications*; a foreword and afterword provide the context for each. As a proof of concept, the refinement of the methodology focuses on the principal case study. This is followed by validation and demonstration of the derived methodological framework (objective 1.3), through application to the principal and four additional case studies. Concluding remarks illustrate how the outcomes of this chapter fit within the wider coupled modelling framework.

1. FOREWORD TO PUBLICATION 1

1.1 MOTIVATION

Hydroecological studies typically focus on inter-annual (year-on-year) and intra-annual (within year) dynamics (Piniewski *et al.*, 2017). Alongside Figure 3-1, the following example will serve to highlight the limitations of this approach.

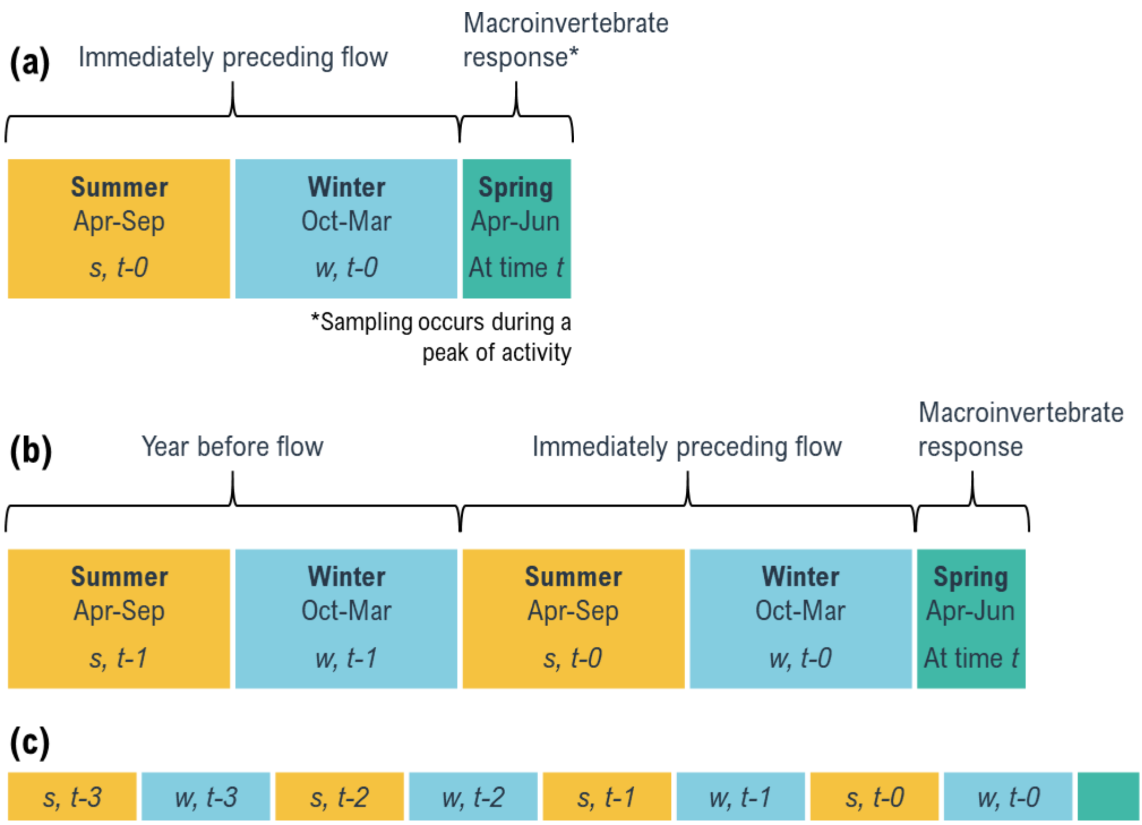

Figure 3-1. Timelines detailing macroinvertebrate response to antecedent flow: *(a)* typical approach capturing inter- and intra-annual dynamics; *(b)* extension of the timeline to include the year before flow; *(c)* extension of the timeline as in publication 1. *Source: Annie Visser-Quinn.*

Hydroecological data sets are created by pairing ecological data (such as the Lotic-invertebrate Index for Flow Evaluation (LIFE) considered here; the associated methodology is detailed in Appendix A, Table A-1-3) with hydrological indicators derived from flow records from the period immediately preceding macroinvertebrate sampling. For instance, the response of macroinvertebrates collected in spring (Apr-Jun) would be considered with reference to flows occurring in the preceding six to twelve months, hydrological winter and summer (Figure 3-1a). This focus on the immediately preceding antecedent flows assumes that an event occurring in the previous summer or winter (year before flow; *t-1*) has no impact on ecological response (Figure 3-1b). By limiting the temporal scale to capture only the inter-annual and intra-annual dynamics, any delayed response of the macroinvertebrate community cannot be accounted for.

A number of studies have observed the presence of this lag in response, primarily in groundwater-fed rivers. Boulton (2003) observed large differences in recolonization following flood and drought events on the Lerderderg River, Victoria, Australia (1982-1986). Recovery time, following a period of drought, took two years, whereas recovery from spate (to pre-flood conditions) occurred within four weeks. Clarke and Dunbar (2005) considered the autumn ecological response to the immediately preceding summer and winter seasons; to account for possible lag, they introduced a six-month seasonal time-offset which they termed 'the summer of the year before'. Further examples include Durance and Ormerod (2007) and Piniewski *et al.* (2014). To date, only limited work has been carried out to directly explore the effects of this lag on the hydroecological relationship, with Bradley *et al.* (2017) and Monk *et al.* (2017) acknowledging the limitations of not accounting for this phenomenon. By not accounting for lag in ecological response, models are failing to capture the true complexities of the hydroecological relationship. Consequently, modelling efforts may be underestimating response; the impact of this would prove even more significant when considered in the context of climate change.

1.2 METHODOLOGY

To satisfy objective 1.1, the first publication, *Macro-invertebrate Community Response to Multi-annual Hydrological Indicators* (Visser *et al.*, 2017), looks to incorporate the protracted temporal scale in the hydroecological modelling. As an initial proof of concept, the focus is on flow exceedance variables representing seasonal low and high flows only (Table 3-1). As in Figure 3-1a, inter- and intra-annual indices represent the immediately preceding flow with a time-offset of six to twelve months. Lag is accounted for by extending this time-offset (following the aforementioned Clarke and Dunbar (2005)) to a maximum of 3-years (Figure 3-1c); initial scoping in Visser (2015) revealed a plateau in the predictive power of the models at this point.

Table 3-1. Matrix of the 16 hydrological indices considered in publication 1.

Hydrological season	*High flow.* The flow exceeded 10% of the time.	*Low flow.* The flow exceeded 95% of the time.
Summer (Apr-Sep)	$Q_{S10}(t)$ $Q_{S10}(t\text{-}1)$ $Q_{S10}(t\text{-}2)$ $Q_{S10}(t\text{-}3)$	$Q_{S95}(t)$ $Q_{S95}(t\text{-}1)$ $Q_{S95}(t\text{-}2)$ $Q_{S95}(t\text{-}3)$
Winter (Oct-Mar)	$Q_{W10}(t)$ $Q_{W10}(t\text{-}1)$ $Q_{W10}(t\text{-}2)$ $Q_{W10}(t\text{-}3)$	$Q_{W95}(t)$ $Q_{W95}(t\text{-}1)$ $Q_{W95}(t\text{-}2)$ $Q_{W95}(t\text{-}3)$

For these 16 hydrological indicators (Table 3-1), a total of 65,535 possible candidate models exist; a stepwise approach (as outlined in *Chapter 1 – 2. State-of-the-art*) reduces this to a more tractable level. The multi-annual aspect of the hydroecological relationship is systematically explored through the application of three approaches with an ascending scale of computational effort. In brief, approach 1 considers 112 candidate models; approach 2 reduces the number of hydrological indicators through the application of principal component analysis (PCA); and approach 3 considers the full suite of 16 hydrological indicators. For each approach, the best models are identified based on their Bayesian Information Criterion score (the weight of evidence in favour of the model), the predictive power of the model (adjusted R-squared) and the data input requirements (years of time-offset). To further explore indicator redundancy, additional factor analysis modelling of the principal components is carried out for the identified best models. The capacity of the hydroecological modelling to incorporate lag is dependent upon the selection of time-offset indicators in the identified best models.

Serving as an initial proof of concept, the above method is applied to the principal case study, the River Nar, a groundwater-fed chalk river in Norfolk, England (Figure 2-1). The author has conducted work on the River Nar previously, looking at macroinvertebrate response to immediately preceding antecedent flow (Visser, 2014). In that work, time series analysis indicated possible delays in recolonization following drought events. Figure 3-2 illustrates this lag in response at site 5, West Acre Road Bridge (52.7 °N, 0.63 °E). It can be seen that, in many cases, these spring (Apr-Jun) LIFE scores take more than 6-12 months to respond to antecedent flows. Samples collected in D and H stand out, with a possible delay in response of 2-years. Consequently, the River Nar represents an ideal case study for exploring whether lag in hydroecological response may be accounted for through the addition of time-offset hydrological indicators.

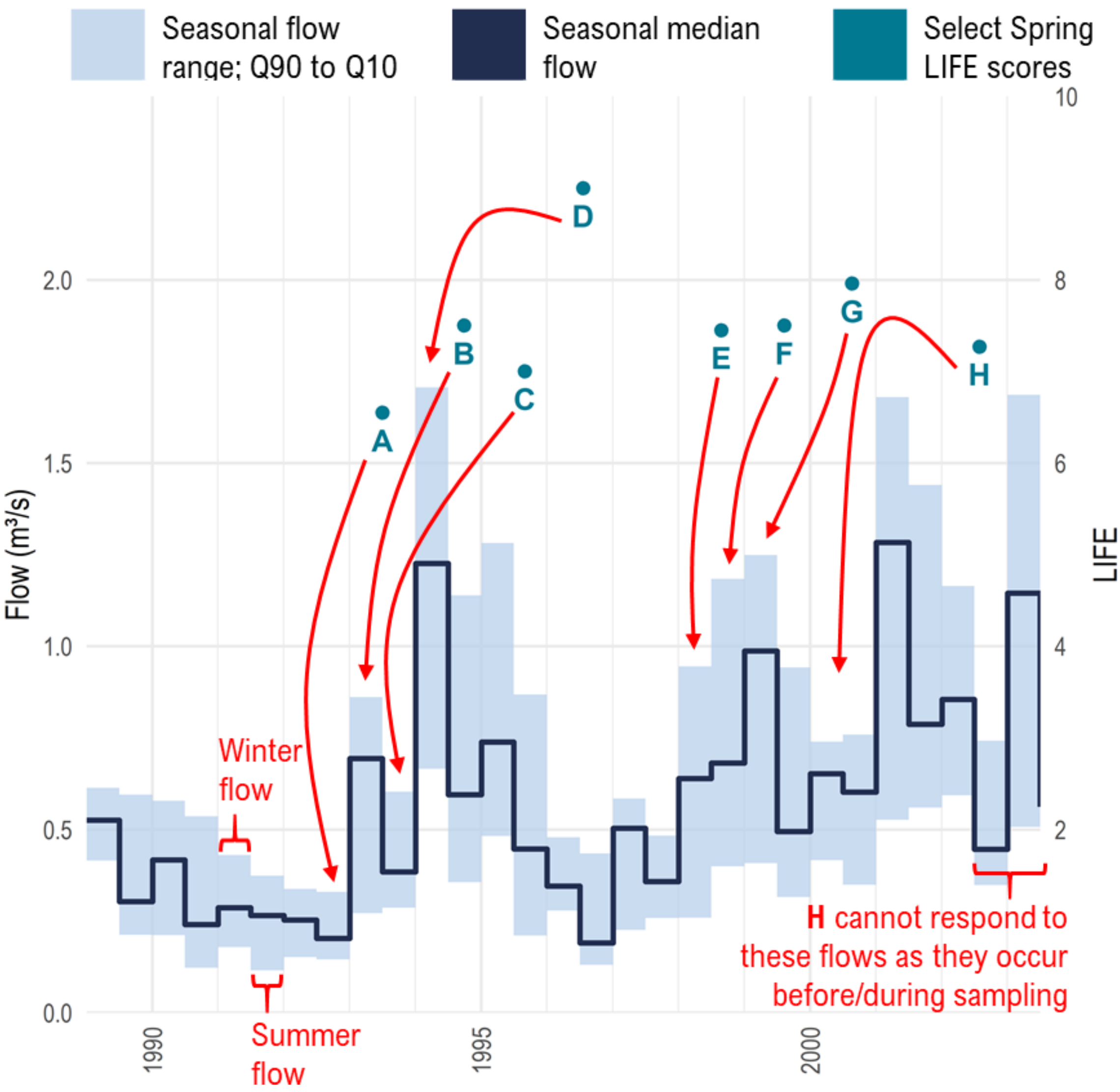

Figure 3-2. Macroinvertebrate response to flow magnitude in the River Nar, at site 5, West Acre Road Bridge. The spring LIFE scores represent a subset from the period 1992-2002. The arrows provide an indication which flows the LIFE scores may be a response to. *Source: Annie Visser-Quinn.*

2. PUBLICATION 1

Visser, A., Beevers, L., & Patidar, S. (2017). Macro-invertebrate Community Response to Multi-annual Hydrological Indicators. *River Research and Applications*, 33, 707-717. doi: 10.1002/rra.3125

For errata, see Appendix C, C-1.

RIVER RESEARCH AND APPLICATIONS
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MACRO-INVERTEBRATE COMMUNITY RESPONSE TO MULTI-ANNUAL HYDROLOGICAL INDICATORS

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ABSTRACT

Flow is widely considered one of the primary drivers of instream ecological response. Increasingly, hydroecological models form the basis of integrated and sustainable approaches to river management, linking flow to ecological response. In doing so, the most ecologically relevant hydrological variables should be selected. Some studies have observed a delayed macro-invertebrate (ecological) response to these variables (i.e. a cumulative inter-annual effect, referred to as multi-annual) in groundwater-fed rivers. To date, only limited research has been performed investigating this phenomenon. This paper examines the ecological response to multi-annual flow indicators for a groundwater-fed river. Relationships between instream ecology and flow were investigated by means of a novel methodological framework developed by integrating statistical data analysis and modelling techniques, such as principal component analysis and multistep regression approaches. Results demonstrated a strong multi-annual multi-seasonal effect. Inclusion of additional antecedent flows indicators appears to enhance overall model performance (in some cases, goodness of fit statistics such as the adjusted R-squared value exceeded 0.6). These results strongly suggest that, in order to understand potential changes to instream ecology arising from changing flow regimes, multi-annual and multi-seasonal relationships should be considered in hydroecological modelling. Copyright © 2017 John Wiley & Sons, Ltd.

KEY WORDS: hydroecology; hydroecological modelling; statistical analysis; river-regime variability; multi-annual; time-offset; groundwater-fed rivers; Lotic-invertebrate Index for Flow Evaluation (LIFE)

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INTRODUCTION

The relationship between flow regime and instream ecological health has been the focus of significant recent research (e.g. Lytle and Poff 2004; Arthington *et al*. 2006; Dudgeon *et al*. 2006; Monk *et al*. 2008; Worrall *et al*. 2014). Freshwater aquatic systems support the provision of many key ecosystem services, including clean (drinking) water, flood protection, food, recreation, wild species habitat and support for interconnected systems (UK NEA 2011). Within the context of the provision of services, there is a clear conflict between the ecological and anthropogenic demands placed upon lotic ecosystems. Since the 1940s, efforts have been made to quantify the minimum flows required to protect freshwater fluvial ecosystems (Arthington *et al*. 2006), leading to the more recent environmental flows research (e.g. Petts 2009). Environmental flows can be defined as the 'quantity, timing and quality of water flows required to sustain [freshwater ecosystems] and the human livelihoods and well-being that depend on these ecosystems' (Hirji and Davis 2009, pp. 13 and 14). It is understood that natural variability in flow is critical for the preservation of aquatic ecosystems (Dudgeon *et al*. 2006) and maintenance of this variability is critical to this research. In order to help balance conflicting requirements often placed on lotic ecosystems, and to further research in the field, accurate modelling is essential.

The use of numerical models (both process and data-driven models) that link flow and freshwater ecological response is a well-established technique for investigating instream response to flow changes (Dunbar *et al*. 2007). Hydrological descriptors and ecological data can serve as the basis for the development of such models (Richter *et al*. 1996; Arthington *et al*. 2006; Monk *et al*. 2008). Macro-invertebrates are particularly sensitive to change (in water chemistry/quality, physical habitat and flow regime) whilst exhibiting a clear response to environmental perturbations, making them ideal biological indicators (Acreman *et al*. 2008; EA 2013). As such, macro-invertebrates (e.g. through standard scoring techniques) commonly serve as a proxy for ecological response and can be linked to hydrological or hydraulic variables in order to test their response to a changing flow regime (e.g. Extence *et al*. 1987; Dunbar and Mould 2009). The Lotic-invertebrate Index for Flow Evaluation (LIFE) is a weighted index taking into account macro-invertebrate community flow velocity preferences (Extence *et al*. 1999), making it well suited for such applications. Hydroecological data sets are created by linking the ecological data (such as LIFE score) with

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hydrological indicators (e.g. mean flow, Q10 and Q95) from the period immediately preceding the sampling. This method has been employed in many studies over the past 2 decades, for example, see Clausen and Biggs (1997), Monk *et al.* (2006), Exley (2006), Monk *et al.* (2008), Dunbar *et al.* (2010) and Worrall *et al.* (2014).

In models, the flow can be expressed as a continuous time series or discrete hydrological indicators representing inter-annual or intra-annual variation (defined as the between year and within year flow components, respectively). If discrete indicators are chosen, then the identified variables must be hydrologically, ecologically, or biologically, relevant. These indicators are frequently identified and refined through statistical approaches such as principal component analysis (PCA) redundancy (Olden and Poff 2003; Monk *et al.* 2008). Where intra-annual variation has been the focus, such as flooding, the conditions immediately preceding sampling tend to be at the exclusive centre of the research (e.g. Greenwood and Booker 2015). This may overlook the cumulative effects of antecedent flow conditions in the preceding seasons and years (Durance and Ormerod 2007), that is, the multi-year, or multi-annual, effect. This is particularly true for rivers with higher Base Flow Indices (BFIs) (groundwater-fed) where there may be a lag in macro-invertebrate community response following extreme hydrological events (i.e. floods and droughts) (Boulton 2003; EA 2005). This lag represents a delayed response of the community to antecedent flow conditions (over seasonal and/or annual timescales). Such lag has been seen to characterize strong ecological responses, specifically in the case of extreme flow disturbances (Wood and Armitage 2004; Wright *et al.* 2004). To date, limited work has been carried out to explore the effects of these lags on the hydroecological relationship (e.g. Clarke and Dunbar 2005). Rivers around the globe derive their streamflow from a variety of sources, including a significant contribution from groundwater/aquifers (although this contribution is highly variable both spatially and temporally). Lags in ecological response within groundwater dominated systems may therefore be of crucial interest.

In order to better model flow variability, and hence improve current understanding of hydroecological relationships for groundwater rivers, this paper aims to examine the presence of lag in the hydroecological relationship (using LIFE scores as a proxy). These relationships are assessed using a long-term (21-year, 1993–2014) paired hydrological and ecological data set for a groundwater dominated system (River Nar, Norfolk, UK). Multi-annual and multi-seasonal flow variables are intended to account for both the cumulative (inter-annual) and seasonal (intra-annual) flow effects.

The multi-annual aspect of the hydroecological relationship (lag) is systematically explored within the proposed statistical modelling framework through the addition of time-offset hydrological variables. Thus, the key objectives are the following:

(1) To identify and develop a suitable statistical modelling framework exploring the multi-annual and multi-seasonal aspect of the hydroecological relationship (a lag in response);
(2) To examine the influence of seasonal low/high flows within the relationship; and
(3) To explore practical channels for wider implementation of the framework.

METHODOLOGY

Study area

The groundwater-fed River Nar (Norfolk, UK; Figure 1), one of southern England's highly valued chalk streams, serves as the focus for this study. The high BFI of the river, the length of the hydroecological data set, and prior observations of lag in ecological response (Visser 2015; Garbe *et al.* 2016) make the Nar an ideal candidate for study.

The River Nar rises in the Norfolk chalk hills 60-m above sea level, flowing west for 42 km, transitioning from steep to a far gentler gradient at Narborough (Figure 1). This topography and underlying geology give rise to two very different ecosystems. Upstream of Narborough, the Nar flows as a (groundwater-fed) chalk river; thereafter, the chalk has been eroded forming a fen basin (Figure 1). This distinctive change at the river's midpoint has led to its designation as a Site of Special Scientific Interest. Because of the presence of the two 'distinct river units', the chalk and fen river sections are considered distinct entities, with the focus of this paper falling on the chalk reach only. The Nar is subject to significant low flow stresses, further amplified by over-abstraction and extensive channel modification, thereby inhibiting the river's ecological potential (NRT 2012).

The River Nar has a BFI of 0.91 (CEH 2014). This dependence on groundwater results in a highly seasonal flow regime; aquifer recharge primarily occurs in autumn, resulting in a progressive rise in river flow until March/April. Chalk rivers are typified by their relatively low flows (Figure 2). For the available record (1953–2015), the average mean flow is 1.133 m^3/s, whereas Q10 and Q95 (the daily streamflow values that are exceeded 10% and 95% of the time) are 2.046 m^3/s and 0.387 m^3/s, respectively (CEH 2014).

Data

Macro-invertebrate biomonitoring data were made available by the Environment Agency (1993–2014) for 10 sites on the River Nar (six of which are situated in the chalk reach) (Figure 1) (EA 2015). For modelling purposes, these data

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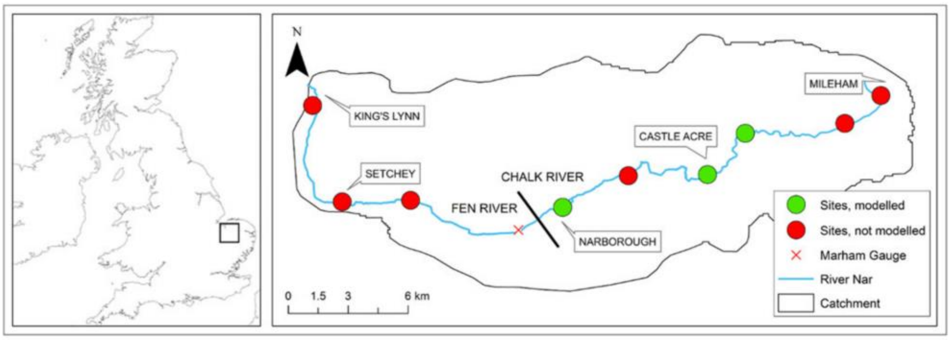

Figure 1. The River Nar and its catchment in the Norfolk Downs, East Anglia; the river flows east to west. The biomonitoring sampling sites are detailed. [Colour figure can be viewed at wileyonlinelibrary.com]

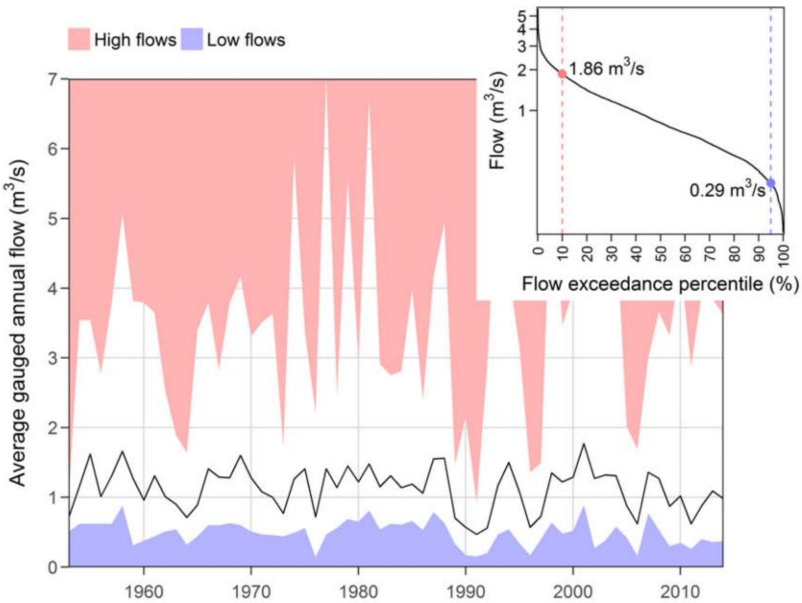

Figure 2. River Nar hydrograph over the available period of record (1953–2014). The black line represents the average annual flow, whilst the red and blue envelopes respectively represent the lowest and highest flows that occurred each year. Inset: flow duration curve for the study period (1989–2014; this is greater than the ecological data set as a result of the time-offset). The dashed lines mark high (Q10) and low (Q95) flows. [Colour figure can be viewed at wileyonlinelibrary.com]

were utilized in the form of LIFE scores. Following Dunbar *et al*. 2006, species level LIFE scores were utilized for both the spring (April–June) and autumn (October–December) seasons, when peaks in macro-invertebrate activity are observed (Lenz 1997). To effectively accommodate the different relationships expected for the spring and autumn macro-invertebrate life cycles, seasons were considered as two separate scenarios (Figure 3). In order to make the site data comparable, the seasonal biotic data were ratio standardized per site.

Daily mean flow data were extracted from the National River Flow Archive for the Marham gauge (TF723119) between 1958 and 2014 (CEH 2014). Typically, a multitude of flow variables is derived (Richter *et al*. 1997); however, in the first instance, this work focuses on basic flow exceedance variables (Q10 and Q95) in order to establish simple interpretation of the hypothesized relationship with multi-annual antecedent flows. Daily flows for the time period (1989–2014; Figure 2) are converted into seasonal (summer: April to September; winter: October to March) flow variables using flow duration analysis. Flow variables are statistically standardized (normalized).

The ecological and the four seasonal flow variables (summer/winter Q10 and Q95) are paired, as is normal (after

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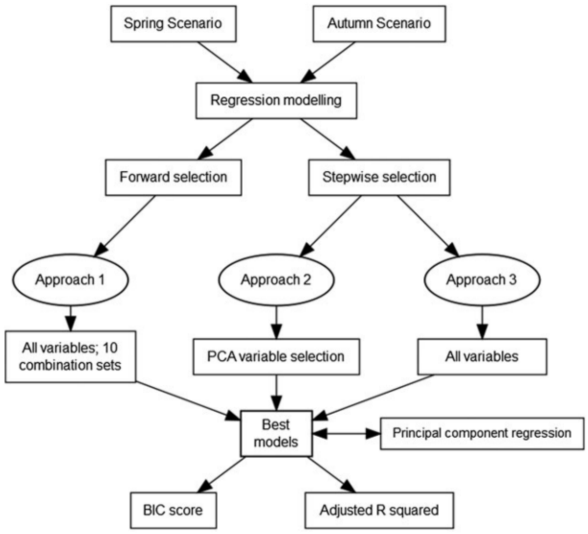

Figure 3. Flow chart detailing the modelling framework employed. BIC, Bayesian information criterion; PCA, principal component analysis

Monk *et al*. 2008), and the data pooled to produce aggregated regression models. To account for the lag in response, these flow variables are time-offset by a year ($t-1$) to a maximum of 3 years ($t-3$) (Table I). Previous work (Visser 2015) trialled a time-offset up to $t-5$ and found that the predictive power of the models plateaued at $t-3$ years. Additionally, adding variables significantly increased computational demands because of an impractical number of variable combinations (Table I).

Data screening

Pressures, resulting in anomalous data points, are known to prevent the detection of relationships between antecedent flow and LIFE score (Clarke and Dunbar 2005). Therefore, those sites affected by issues such as low water quality, sediment ingress, sampling issues or other sources of variability were excluded from this work; a total of three sites were removed. Removal criterion was in accordance with Clarke and Dunbar (2005, p. 16), Dunbar *et al*. (2006, pp. 1 and 2) and Dunbar and Mould (2009, pp. 1–3).

Table I. Summary of the number of variables, and subsequent possible combinations, for each additional year of time-offset antecedent flow

	No. of variables	No. of combinations
t	4	15
$t-1$	8	225
$t-2$	12	4095
$t-3$	16	65 535

Each year features four variables: summer/winter Q10 (high flow) and Q95 (low flow).

Modelling and statistical analysis

The aim of multistep regression modelling is to assess a complete suite of candidate models (which can be obtained from different combinations of response variables in the modelling runs) and to identify the candidates that are both statistically significant and offer sufficient predictive power. Here, a model represents any candidate that achieves significance ($p > 0.05$). In the context of the present paper, models should encompass lag in the hydroecological relationship with LIFE. The potential for a multi-seasonal aspect to the relationship was assessed via various combinations of the seasonal flow variables (summer and winter). The putative multi-annual aspect was considered via the introduction of their associated time-offset flows.

To effectively integrate multi-seasonal and/or multi-annual aspects of antecedent flows into the hydroecological relationship, the proposed modelling framework integrated up to 16 variables, shown in Table I. The derivation of this framework is summarized in Figure 3. All analysis was performed using R, an open source software environment for statistical programming and graphical analysis (R Core Team 2016); where a pre-existing package was employed, it is referenced as appropriate.

Multistep (or multistage) regression modelling is a popular technique for reducing the number of predictor variables in large data sets (Wasserman and Roeder 2009). In each step, regression of different variable combinations is considered, resulting in a number of candidate models. The variable combinations are determined by the method applied: forward, backward or stepwise selection. Forward selection is the simplest of the three, where variables are added one at a time and the variable's contribution to the candidate model is assessed against a threshold or stopping point. When a variable has been added to the candidate model, it cannot be removed. In backwards selection, the variables are removed one at a time, but here, the variable with the smallest contribution is removed at each step. Stepwise selection is the most exhaustive of the three, where variables may be both added and removed at each step.

Here, three different approaches were considered, using both forward (approach 1) and stepwise selection (approaches 2 and 3) on three subsets of the hydrological variables; these are summarized in Figure 3 and discussed next. The presence of any lag in the hydroecological relationship was first identified using the simplest and broadest statistical methods. The initial variable subset provides an overall view, consisting of the combinations of two seasonal variables (and their associated time-offsets), summarized in

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Table II. These candidates are considered through the application of forward selection.

This was followed by two, more sophisticated, stepwise approaches (Figure 3), with the focus on optimizing the modelling. The stepwise selection was applied using the R package 'leaps' (Thomas Lumley using Fortran code by Alan Miller 2009), using the object '*leaps.exhaustive*' to determine the best model variable combinations. One of the first tasks in hydroecological modelling is to reduce the level of hydrologic variable redundancy, thereby simplifying the analyses. To this end, PCA for variable selection (after Olden and Poff 2003) was applied, using broken-stick as the stopping rule (Jackson 1993). This PCA-reduced variable subset was modelled in the second approach (Figure 3).

Monk *et al*. (2007, p. 113) cast doubt over the use of PCA for hydrological variable selection, stating that it is necessary to 'exercise caution when employing data reduction/index redundancy approaches, as they may reject variables of ecological significance'. Greater scepticism arises because the approaches taken here depart markedly from other work. Therefore, seeking completeness, the full set of 16 variables was considered for the final iteration (Figure 3, approach 3).

Table II. The sets of seasonal variable combinations considered for approach 1, the initial variable subset

Set	Seasonal variables		No. of combinations
1	Summer Q10	—	4
2	Summer Q95	—	4
3	Winter Q10	—	4
4	Winter Q95	—	4
5	Summer Q10	Summer Q95	16
6	Winter Q10	Winter Q95	16
7	Winter Q10	Summer Q95	16
8	Winter Q95	Summer Q10	16
9	Winter Q95	Summer Q95	16
10	Winter Q10	Summer Q10	16

Multistep regression techniques are often criticized because of their (frequently) automatic nature and concerns over the robustness of the selection algorithm (Wasserman and Roeder 2009). For example, this lack of user interaction can lead to convergence on a poor model. Here, model selection was assessed semi-automatically via a custom algorithm requiring user input; this dialogue helps retain the awareness of the user during the multistep process. The 'best' models were then selected on the basis (in order of importance) of their Bayesian information criterion (BIC) score, the power of the model ($\overline{R}^2$) and the data input requirements. BIC is an assessment of the relative 'goodness' of models based upon log-likelihood and penalty terms (Raftery 1995), thereby allowing the selection of the simplest model whilst not sacrificing accuracy excessively. The criterion provides a measure of the weight of evidence in favour of particular models. The goodness of fit, R-squared (R^2), is not presented because of a tendency for overfitting in multiple regression models (Yin and Fan 2001). To account for this, the adjusted R-squared ($\overline{R}^2$) [based upon the frequently used Wherry formula-1 (Yin and Fan 2001)] is quoted instead.

The power or fit of models can potentially be improved through the removal of redundancy and/or noise using PCA, where it allows the user to retain most of the variability in the data through the first few components.

Table III. Summary statistics for the best models from each approach for the spring scenario

		Best models			Factor models		
Model	Flow data (years)	$\overline{R}^2$	*ΔBIC*	Weight of evidence	$\overline{R}^2$	*ΔBIC*	Weight of evidence
S1.1	2	0.28	6.2	Strong	0.28	6.2	Strong
S1.2	2	0.25	4.7	Positive	0.25	4.7	Positive
S1.3	2	0.27	3.5	Positive	0.30	7	Strong
S2.1	2	0.28	6.1	Strong	0.28	6.1	Strong
S2.2	2	0.21	5.5	Positive			
S2.3	2	0.20	5.2	Positive			
S2.4	1	0.20	5	Positive			
S2.5	2	0.24	4.3	Positive	0.26	7.8	Strong
S3.1	4	0.60	17.6	Very strong	0.23	0.0	Weak
S3.2	4	0.58	17.4	Very strong	0.19	0.0	Weak
S3.3	4	0.63	17	Very strong	0.20	0.0	Weak
S3.4	4	0.57	16.9	Very strong	0.18	0.0	Weak
S3.5	4	0.63	16.7	Very strong	0.21	0.8	Weak

The $\overline{R}^2$ column is the adjusted R-squared, and the weight of evidence is Raftery's (1995) grading of model quality based on *ΔBIC*. The reduced dimension factor models for each of these are presented on the right; where models consist of only one variable, no factor model is possible.

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The stopping point was determined using the broken-stick. Factor selection modelling, essentially regression models composing of the principal components, was then applied as before.

RESULTS

Three approaches to the modelling were considered. Each approach was applied to two distinct scenarios, spring and autumn; results from these scenarios should be considered as distinct. Because of the large numbers of models produced, only the five 'best' models are discussed (selected by the supporting weight of evidence, *ΔBIC*). The first approach is an exception, because of the reduced number of candidates, and only the three best models are presented. The model naming convention references the scenario, approach number and model ranking. *For example, model S3.1 is a model from the spring scenario, derived using the third approach, and is the best model from that approach.*

Approach 1—initial variable subset

The first approach was based upon a subset considering all of the hydrological variables. The number of candidates was limited to 112 (Table II) as the purpose of this first approach was to determine the presence of lag in the hydroecological relationship. The summary statistics associated with the three best models are summarized in Tables III and IV, for the spring and autumn scenarios, respectively. The model structures are summarized in Figure 4.

Principal component analysis was applied to the best models from each scenario. Factor models were then produced from the most relevant principal components (determined using the broken-stick method). The associated summary statistics are also included in Tables III and IV.

Approach 2—principal component analysis-reduced variable subset

In this iteration, PCA for variable reduction was applied. The spring and autumn scenarios variable subsets were reduced from 16 to 6 as follows:

Spring: $Q_{S10}(t)$, $Q_{S95}(t-1)$, $Q_{W10}(t-1)$, $Q_{W10}(t-3)$, $Q_{W95}(t-1)$ and $Q_{W95}(t-3)$;

Autumn: $Q_{S10}(t)$, $Q_{S10}(t-3)$, $Q_{S95}(t)$, $Q_{S95}(t-3)$, $Q_{W10}(t-1)$ and $Q_{W95}(t-1)$.

The total number of candidate models was reduced to 63, this time considered through stepwise selection. The summary statistics associated with the five adjudged best models for the spring scenario are summarized in Table III; the model structures are summarized in Figure 4. No models were derived for the autumn scenario. The summary statistics for the reduced dimension factor models are also available in Table III.

Approach 3—all variables

This final approach considered all 16 hydrologic variables, for a total of 65 535 *possible* candidates. Stepwise selection reduced this to a manageable scale. The summary statistics associated with the five best models, from each scenario, are summarized in Tables III and IV. The model structures are summarized in Figure 4. The summary statistics for the reduced dimension factor models are available in Tables III and IV.

DISCUSSION

Approach 1—initial variable subset

The primary aim of the first approach was to detect if lag in the hydroecological relationship for LIFE was present. Tables III and IV show this to be true. In fact, out of 224

Table IV. Summary statistics for the best models from each approach for the autumn scenario

Model	Flow data (years)	Best models $\overline{R}^2$	Best models *ΔBIC*	Best models Weight of evidence	Factor models $\overline{R}^2$	Factor models *ΔBIC*	Factor models Weight of evidence
A1.1	2	0.44	10.7	Very strong	0.44	10.7	Very strong
A1.2	2	0.45	9.3	Strong	0.45	9.3	Strong
A1.3	2	0.40	9.0	Strong	0.40	9	Strong
A3.1	2	0.46	13.6	Very strong			
A3.2	2	0.48	12.8	Very strong	0.29	6.6	Strong
A3.3	2	0.46	11.5	Very strong	0.47	14.2	Very strong
A3.4	2	0.49	11.2	Very strong	0.26	5.4	Positive
A3.5	2	0.44	10.8	Very strong	0.44	10.8	Very strong

The $\overline{R}^2$ column is the adjusted R-squared, and the weight of evidence is Raftery's (1995) grading of model quality based on *ΔBIC*. The reduced dimension factor models for each of these are presented on the right; where models consist of only one variable, no factor model is possible. The second approach (principal component analysis-reduced variable subset; A2) featured no models.

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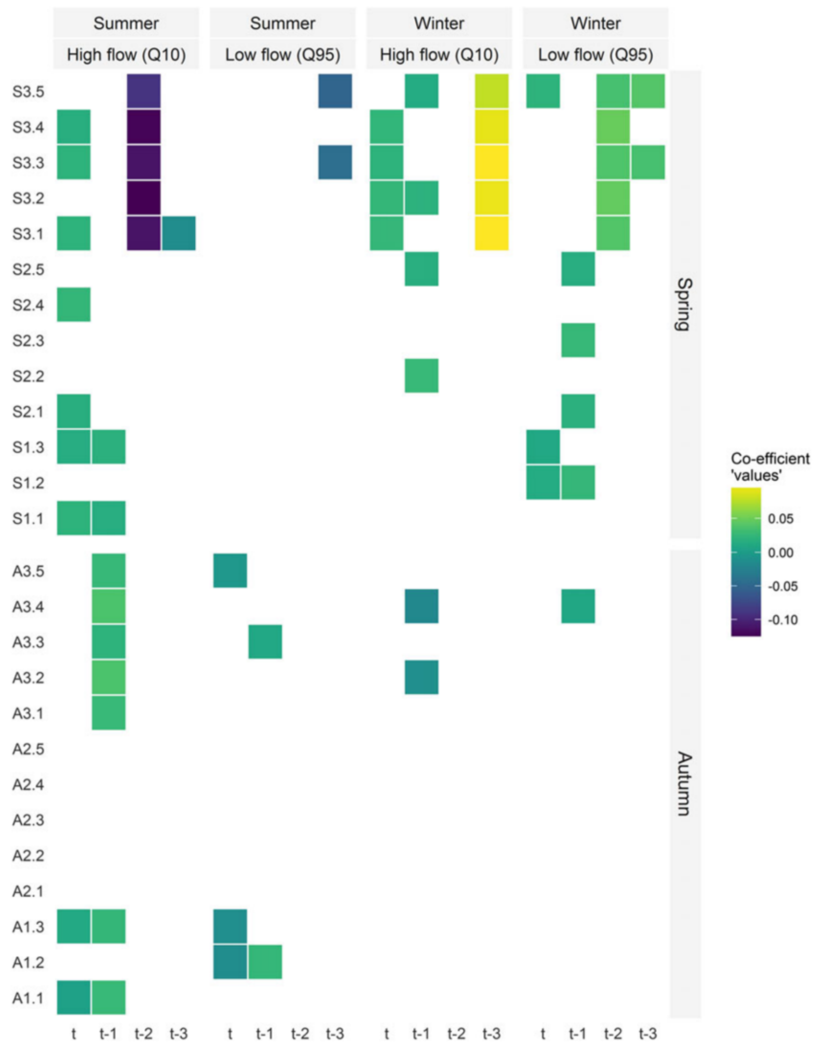

Figure 4. Heatmap detailing the structure (i.e. which variables are included) and scale of coefficients for the best models from each approach (per scenario). (Note: model *y*-intercepts are approximately equal to 1.) Model names correspond to Tables III and IV. [Colour figure can be viewed at wileyonlinelibrary.com]

combinations (for both scenarios), there were 147 of the candidates represented viable models (i.e. achieved significance).

In the case of the spring scenario, the weight of evidence is relatively low for models S1.2 and S1.3, whereas the adjusted R-squared is similar for all three (Table III). This example clearly illustrates the important role of BIC in selecting the best models. Regarding the model structure (Figure 4), summer Q10 flows feature most strongly, whereas the presence of winter Q95 variables illustrates the critical nature of winter low flows.

The factor models composed of the principal components may or may not improve the interpretability of the data. In this case, the models were identical for S1.1 and S1.2 (Table III), whereas S1.3 showed improvement both in the weight of evidence and adjusted R-squared. This improvement suggests that it is the strongest model available for the spring scenario. By reducing redundancy, a more efficient model is produced. This is particularly encouraging as it is a purely procedural change with no further data requirements.

For the autumn scenario, the weight of evidence in favour of the three best models is considerably increased (Table IV). This represents the best possible outcome in terms of confirming the presence of lag in the hydro-ecological relationship. It should be noted that although model A1.1 achieves the highest BIC weighting, it does not feature the highest adjusted R-squared (as seen

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previously for the spring scenario). The autumn models show no relationship with winter flows, rather they relate more strongly with summer (Figure 4). The factor models show no change, being identical to the best models (Table IV).

Approach 2—principal component analysis reduced variable subset

After confirmation of the presence of the hypothesized relationship, this first iteration sought to improve upon the methods and models via reduced redundancy. The redundant variables were removed through Olden and Poff's (2003) 'PCA redundancy approach', reducing the number of variables from 16 to 6 for both scenarios. For this approach, a broader range of candidates is considered through stepwise selection.

Here, the models for both scenarios are unsatisfactory (Tables III and IV). They exhibit no overall improvement over those produced using the more limited methodology of approach 1. Only the factor model for S2.5 shows an improvement in the weight of evidence. There is limited value in a lengthy consideration of these models because of their poor quality. Examination of the variable subsets for spring in approaches 1 and 2 (see Table II and section on Approach 2—Principal Component Analysis-reduced Variable Subset) suggests that the PCA did not capture the ecologically relevant variables, a concern cited by Monk *et al*. (2007) previously. (Monk concluded that subtle factors beyond the dominant sources of statistical variation may be more influential.) This argument is further bolstered by the fact that the autumn candidates were unable to present any significant combinations.

Approach 3—all variables

In light of the results from approach 2, and for the sake of completeness, a final iteration considering all 16 variables was applied. The weight of evidence in favour of the best models produced in this final iteration shows it to be the most successful in capturing the LIFE-correlated lagged hydroecological relationships (Tables III and IV). The models for the spring scenario are most notable, with the BIC weight of evidence exceeding Raftery's (1995) highest grading. The corresponding adjusted R-squared for each model is similarly positive. This is particularly interesting when compared with corresponding values presented in the literature: multiple catchment studies such as Clarke and Dunbar (2005), Dunbar *et al*. (2006) and Monk *et al*. (2007) achieved values of between 0.2 and 0.3; despite focussing on the River Itchen exclusively, Exley (2006) also achieved values of around 0.3. For this scenario, again, the factor models provided no improvement.

The approach 3 spring scenario models were best overall. In particular, they show considerable improvement over those from approach 1. In light of this, it is not surprising that variable inclusion in the models has evolved (Figure 4). However, the focus on summer high flows remains, featuring the largest coefficients (Figure 4). Given that spring and summer months tend to be a very active period for macro-invertebrates (Lenz 1997), it therefore follows that summer flows have a strong influence over spring LIFE scores, and by extension, ecosystem health. The observed negative relationship with summer flows (beyond the immediately preceding antecedent flow, t) suggests that naturally occurring high and low flows exert a moderating effect on LIFE scores (Lytle and Poff 2004). As discussed prior, the emphasis on winter flows highlights their importance for aquifer recharge and, by extension, LIFE scores.

The best models for the autumn scenario also occur as a result of the third approach (Table IV). Despite a lower overall quality of models, the reduced number of variables (Figure 4), and hence data requirements, is appealing. Again, the models retain a very strongly positive predication upon summer high flows, here some orders of magnitude greater than the others. The models also reveal a strongly inverse influence of winter low flows ($t-1$) (Figure 4). This flow is that which occurs at the time of the autumn macro-invertebrate sampling.

The autumn factor models exhibit an improvement for one case, S3.3, resulting in the best overall model. This highlights that, although there are no guarantees that factor models will improve model quality, there is some value in its implementation, particularly as it requires no additional data requirements.

Implications

This work illustrates clearly the significance of accounting for lag (in the form of multi-annual and multi-seasonal flow variables) in the LIFE hydroecological relationship (in the River Nar). Of the 26 best models identified, only three relied on the direct antecedent flow (i.e. utilized one previous year of flow data). Further, overall, these were some of the poorest models produced (in terms of the model quality, BIC). This suggests that, in this case of a groundwater-fed river, it could be presumed that a single year of antecedent flows overlooks critical information.

The principal difficulty in the use of the multi-annual and multi-seasonal flow variables could be the potential data requirements. This work suggests that, for effective modelling of the spring scenario, a consistent suite of 4 years of data is required (Table III). In contrast, the autumn scenario requires much less input with just 2 years (Table IV). However, it is made clear that, by accounting for the

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multi-seasonal multi-annual variation in flow in the modelling framework, the models can be significantly improved through better representation of the natural variability of the river system. An understanding of which is fundamental to active maintenance of any riverine system's ecological integrity (Petts 2009).

Incidentally, the methods employed also highlight the need to consider more comprehensive statistical approaches when embarking on modelling of this type. The failure of approach 2, where PCA was used to identify variable redundancy, further stresses the need to exercise caution. The authors would thus promote consideration of modelling both with and without this redundancy technique. This is not to say that PCA techniques have no application potential; the factor models did (on occasion) provide some improvement to the best models.

Considering the wider impact of the present work, modelling the ecological season plays an important role. This choice is typically made based upon the goals of the modelling. For example, brown trout is a key species in the River Nar, being valued highly by the local fisherman (Garbe *et al.* 2016). One of their primary food sources is the Mayfly (*Ephemeroptera baetidae*) that hatch during the spring season. Therefore, in the Nar, if environmental flows were to be set to promote brown trout population, the focus of the modelling efforts should surround spring. It may also be possible that the consideration of additional, more ecologically relevant, hydrological variables [selected through the Indicators of Hydrologic Alteration method (Richter *et al.* 1996)] may reduce data requirements. (The application of the Indicators of Hydrologic Alteration forms part of the body of future work.) However, this may simply be dependent upon the type of river under consideration.

The outcomes of this work appear particularly pertinent to water resource planning and environmental flows research. Better understanding of longer-term hydroecological relationships allows for enhanced resilience. This is particularly relevant in the case of climate change where the outlook is uncertain. The simple application of the methods applied herein, easily replicated using R, or another programming language, makes it both accessible and replicable. It is hoped that this can be simplified further still in the future through a framework or package. However, before it can be considered for general use, there is need for further work considering other more ecologically relevant hydrologic variables as well as application to other rivers.

CONCLUSIONS

The variability of the natural flow regime, particularly floods and droughts, is known to be critical to ecological health (Lytle and Poff 2004). For rivers with a higher BFI (groundwater-fed), there may be lags in ecological response to this variability (Boulton 2003). Currently, the majority of research focuses on the inter-annual hydrologic variation that immediately precedes ecological sampling, and in neglecting a broader temporal view, may be failing to present a true picture of the reality. The research presented herein has taken a multi-annual (cumulative inter-annual) and multi-seasonal (direct intra-annual) approach, using a groundwater-fed river with a high BFI to explore these patterns (using simple hydrological variables as proof of concept).

The first aim of this study was to identify whether there was a multi-annual LIFE-correlated hydroecological relationship in evidence in the case study river, the River Nar. The dimensionality of the data set required the derivation of a new methodology, explored through three approaches. Two scenarios were considered in order to account for the different macro-invertebrate life cycles. The best and strongest relationships were seen to occur for the spring scenario, using the third approach. Relative to other studies (e.g. Clarke and Dunbar 2005; Dunbar *et al.* 2006; Exley 2006; and Monk *et al.* 2007), the strength end of these relationships is strongly suggestive of a positive multi-annual hydroecological relationship.

The second priority was to examine which flows resulted in the strongest relationships. Throughout, the best models featured primarily high flows. It is thought that the reasons for this could be due to the relatively high variation of high flows when compared with low flows. Unexpectedly, the most critical high flows appeared to occur in summer as opposed to winter when aquifer recharge occurs. However, these findings do not suggest that winter aquifer recharge is unimportant as the magnitude of summer high flows is ultimately dependent upon this recharge. The importance of low flows is also evident.

Finally, the findings suggest that the additional hydroecological data requirements may vary. For the spring scenario, a total of 4 years of antecedent flow data would be required, whereas for autumn, only 2 years were required. This reduction in data input was however at the cost of model power. This study focussed on simple hydrological variables. Further work should broaden this data set, and consider further river types, and in so doing, the ecological relevance of the lag may differ.

An incidental conclusion of the work was the role of PCA. PCA is frequently used to reduce hydrologic variable redundancy. Concerns regarding this approach have been raised in the past (Monk *et al.* 2007) with the findings here supporting this (approach 2). However, the use of factor models (principal component regression modelling; approach 3) showed positive results in some situations. This is of particular interests because it requires no additional data.

Overall, this research has demonstrated the presence of a positive multi-annual hydroecological relationship. These

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results confirm that current methods that focus on inter-annual and intra-annual relationships in their current format (immediately preceding ecological sampling) relationships may underestimate the response. Consideration of a broader temporal scale, with a more comprehensive statistical approach, appears likely to result in a more complex understanding of ecological response.

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3. AFTERWORD TO PUBLICATION 1

This first publication has shown that it is possible to consider lag in hydroecological response through the addition of time-offset hydrological indicators, thereby satisfying objective 1.1. Thus, it is possible to show that, for the case study river, macroinvertebrates are influenced by more than just the immediately preceding flows. Of the best models identified, only 11% focussed, exclusively, on immediately preceding flows; they were also amongst the, relatively, poorest. The present focus of hydroecological studies on immediately preceding flows may thus be overlooking critical information.

Despite the benefits observed, the need for time-offset hydrological indicators could represent a significant constraint due to increased data requirements. For instance, if indicators offset by up to *t-3* years are identified as ecologically relevant, the number of data points is reduced by three years. This is of concern given the typically short time series of available macroinvertebrate data (< 20 years) (Monk *et al.*, 2006; Knight *et al.*, 2008). This raises the question as to whether the benefits of an improved understanding of the hydroecological relationship outweighs the impact upon modelling robustness.

Publication 1 has shown that hydroecological models can capture this additional complexity. However, this work provides no indication of the impact of this reduced parsimony; this is considered via objective 1.2 in publication 2. Additionally, it is necessary to determine whether lag is relevant across a range of hydrologically diverse catchments, or only in groundwater-fed catchments such as the River Nar. This is the focus of objective 1.3 and is addressed in *7. Validation*.

4. FOREWORD TO PUBLICATION 2

4.1 MOTIVATION

The development of the coupled modelling framework requires the characterisation and minimisation of uncertainty. Publication 1 highlighted an increasing understanding of the complexity inherent to the hydroecological relationship. The uncertainty revealed thus requires some reconsideration as to the suitability of the current approach to hydroecological modelling. These concerns are reflected in objective 1.2, and addressed through the second publication, *Complexity in hydroecological modelling: A comparison of stepwise selection and information theory* (Visser *et al.*, 2018).

Hydroecological models are, typically, derived through stepwise regression (see *Chapter 1 – 2. State-of-the-art* and publication 1). An algorithm adds and/or subtracts variables (in this case, hydrological indices) according to identified criteria. The algorithm stops once a specified stopping criterion has been met, resulting in a single model output. The assumption is that this single model represents the so-called 'best' model with the most predictive power. Burnham *et al*. (2011) posit that the popularity of stepwise methods lies in their *"longer exposure in science"*, along with the inherent straightforwardness and accessibility of the approach.

The limitations of stepwise methods are growing increasingly recognised and acknowledged (Whittingham *et al.*, 2006; Wasserstein and Lazar, 2016), but not, it appears within hydroecological modelling. On the subject of good statistical practice, Wasserstein and Lazar (2016), state that it is *"as an essential component of good scientific practice"* (p. 132). In other disciplines, the consensus advice is to focus on methods which address the effect size, uncertainty and the weight of evidence supporting the hypothesis (Burnham and Anderson, 2002; Stephens *et al.*, 2005; Whittingham *et al.*, 2006; Burnham *et al.*, 2011; Wasserstein and Lazar, 2016). As prompted by this literature, when asking what methods can satisfy these requirements, a look to the field of information theory is most strongly indicated. Information theory is concerned with the mathematical theory of probability and statistics (Pierce, 2012). It consists of two parts: information which the data can supply about some unknown parameter; and entropy, the amount of information conveyed (i.e. a measure of uncertainty) (Cover and Thomas, 2005). With the assistance of these simple concepts, one may attempt to build robust and statistically defensible models.

Further modelling approaches, such as generalised linear mixed models and lasso & ridge regression, have also been explored. However, with limited data availability, too complex a model would inevitably result in a poor representation (Lele and Dennis, 2009) of the future. As highlighted in Bolker (2009), these *"small, noisy data sets can only answer simple, well-posed questions"* (p. 590).

4.2 METHODOLOGY

The second publication assesses the performance of both stepwise selection, and the proposed alternative approach, information theory, in a hydroecological setting. Acting as further refinement of the hydroecological modelling, the focus is, again, on the principal case study, the River Nar. Establishing the wider applicability of the methodology is established through objective 1.3 at the close of this chapter. An overview of the information theory methodology, as well as the hydrological indicators considered, is first presented.

4.2.1 Information theory

The information theory approach provides a quantitative measure of support, the likelihood that a candidate model is the best approximating model. Inference is made from multiple models through model averaging. Details of the evaluation of the candidate models is provided below. In summary: (1) the candidate models are evaluated with respect to the second-order bias corrected Akaike Information Criterion (after Burnham and Anderson (2002); (2) evidence in support of the candidat e models is determined; (3) a best approximating model is inferred from a weighted combination of all the candidate models. Models parameters (hydrological indices) may be ranked, such that the highest value represents the most important in the model.

Step 1 – Loss of information from model f

Kullback-Leibler distance is a measure of the amount of information lost when model *g* is used to approximate reality, *f*. The model with the least information loss, i.e. the greatest supporting evidence of the candidate models, is considered the best approximation of reality.

The information loss, *I(f,g)*, is determined through computation of an information criteria. According to Burnham & Anderson (2002), both Akaike and Bayesian Information Criteria (AIC and BIC) are commonly used to guide model selection. In actuality, BIC is a misnomer; it does not provide a measure of Kullback-Leibler information, rather, it provides a measure of the evidence *against* the candidate model. In doing so, BIC assumes that a true model does exist. Further, the penalty term in BIC leads to underfitting in smaller sample sizes. The selection of the appropriate information criterion is therefore a philosophical, as well as practical, concern.

With the above in mind, this thesis, and framework, utilises AIC as the measure of information loss. The objective of AIC is to maximise the log-likelihood function, whilst minimising the number of parameters, *K*; the problem is turned into one of minimisation through consideration of negative log:

$$AIC = -2log\ likelihood + 2K$$

where *2K* is a penalty term.

In hydroecological modelling, the sample size is often small relative to the number of variables. In such situations, Burnham & Anderson, (2002) recommend the use of a second order bias correction, AICc:

$$AIC_c = -2log\ likelihood + 2K\left(\frac{n}{n-K-1}\right)$$

In effect, the previous penalty term is multiplied by an additional correction factor which considers the sample size, *n.*

Step 2 – Evidence in support of model g_i

Model AIC_c is rescaled and ranked relative to the minimum value:

$$\Delta_i = AIC_{c_i} - AIC_{c_{min}}\ for\ i = 1, 2, \dots, R.$$

This provides a measure of evidence, from which the *likelihood* that model g_i is the best approximating model can be determined. This is known as the Akaike weight, w, ranging from 1 to 0, for the most and least likely models respectively:

$$w_i = \frac{exp\left(-\frac{1}{2}\Delta_i\right)}{\sum_{r=1}^{R} \exp\left(-\frac{1}{2}\Delta_r\right)}$$

Step 3 – Multi-model inference

The best approximating model is inferred from a weighted combination of all the candidates; with a small sample size, *n*, the assumption is that all models in the set have normally distributed errors (residuals). Parameter averages, $\hat{\hat{\theta}}$, are the sum of the Akaike weights for each model containing the predictor, $\hat{\theta}$:

$$\hat{\hat{\theta}} = \sum_{i=1}^{R} w_i \hat{\theta}_i$$

Parameter averages are ranked, such that the highest value represents the most important in the model.

In this thesis, the information theory approach is applied using the R package *glmulti* (Calcagno, 2013). To ensure convergence on the most suitable candidate set, glmulti is applied five times and the multi-model average derived (Calcagno and de Mazancourt, 2010). Filters are applied to remove parameters (hydrological indices) where the estimate and confidence intervals are zero (i.e. certainty that the parameter is not to be included) and to reduce the model to the parameters which describe 95% of the cumulative information.

4.2.2 Hydrological indicators

As in publication 1, the hydrological indices focus on flow exceedance only (Table 3-2); additional indicators representing moderate high & low and median flows are also considered. The publication considers two scenarios; the first focusses on inter-annual hydrological indicators only, whilst the second accounts for lag in ecological response through the addition of time-offset hydrological indicators, (based on the findings in publication 1, the maximum time-offset is reduced to 2-years (*t-2*)). Through application of both methods, it is intended that both relative, and absolute, limitations of the stepwise approach be highlighted. In doing so, the method which provides the most robust and complete picture of the hydroecological relationship may be determined.

Table 3-2. Matrix of the hydrological indices considered in publication 2. The first scenario considers only those indicators marked with an asterisk (*); all 30 indicators are considered in the second scenario.

Hydrological season	*High flow*	*Moderate high flow*	*Median flow*	*Moderate low flow*	*Low flow*
Summer (Apr-Sep)	$Q_{S10}(t)$* $Q_{S10}(t\text{-}1)$ $Q_{S10}(t\text{-}2)$	$Q_{S25}(t)$* $Q_{S25}(t\text{-}1)$ $Q_{S25}(t\text{-}2)$	$Q_{S50}(t)$* $Q_{S50}(t\text{-}1)$ $Q_{S50}(t\text{-}2)$	$Q_{S75}(t)$* $Q_{S75}(t\text{-}1)$ $Q_{S75}(t\text{-}2)$	$Q_{S90}(t)$* $Q_{S90}(t\text{-}1)$ $Q_{S90}(t\text{-}2)$
Winter (Oct-Mar)	$Q_{W10}(t)$* $Q_{W10}(t\text{-}1)$ $Q_{W10}(t\text{-}2)$	$Q_{W25}(t)$* $Q_{W25}(t\text{-}1)$ $Q_{W25}(t\text{-}2)$	$Q_{W50}(t)$* $Q_{W50}(t\text{-}1)$ $Q_{W50}(t\text{-}2)$	$Q_{W75}(t)$* $Q_{W75}(t\text{-}1)$ $Q_{W75}(t\text{-}2)$	$Q_{W90}(t)$* $Q_{W90}(t\text{-}1)$ $Q_{W90}(t\text{-}2)$

5. PUBLICATION 2

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For errata, see Appendix C, C-2.

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RESEARCH ARTICLE

WILEY

Complexity in hydroecological modelling: A comparison of stepwise selection and information theory

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Abstract

Understanding of the hydroecological relationship is vital to maintaining the health of the river and thus its ecosystem. Stepwise selection is widely used to develop numerical models which represent these processes. Increasingly, however, there are questions over the suitability of the approach, and coupled with the increasing complexity of hydroecological modelling, there is a real need to consider alternative approaches. In this study, stepwise selection and information theory are employed to develop models which represent two realizations of the system which recognizes increasing complexity. The two approaches are assessed in terms of model structure, modelling error, and model (statistical) uncertainty. The results appear initially inconclusive, with the information theory approach leading to a reduction in modelling error but greater uncertainty. A Monte Carlo approach, used to explore this uncertainty, revealed modelling errors to be only slightly more distributed for the information theory approach. Consideration of the philosophical underpinnings of the two approaches provides greater clarity. Statistical uncertainty, as measured by information theory, will always be greater due to its consideration of two sources, parameter and model selection. Consequently, by encompassing greater information, the measure of statistical uncertainty is more realistic, making an information theory approach more reflective of the complexity in real-world applications.

KEYWORDS

complexity, ecological lag, hydroecological modelling, information theory, regression, statistical uncertainty, stepwise selection, uncertainty

1 | INTRODUCTION

The ecological role of flow is increasingly understood. Rivers are not solely dependent on low flows; they represent extremely variable and dynamic systems (Arthington, 2012; Poff et al., 1997). It is widely acknowledged that the flow regime is a major determinant of the ecological health of river ecosystems (Lake, 2013; Lytle & Poff, 2004; Poff et al., 1997; Poff & Zimmerman, 2010). The inherent complexity makes it challenging to identify and quantify hydroecological relationships.

Numerical modelling is a well-established technique for testing hydroecological hypotheses. Hydroecological models can be developed at different scales, from the single case study river model (Exley, 2006; Visser, Beevers, & Patidar, 2017) with multiple sample sites to models encompassing a given region or particular flow regime (Monk, Wood, Hannah, & Wilson, 2007; Worrall et al., 2014). Ecological data and hydrological (ecologically/biologically relevant) predictors serve as the basis for these models. The ecological component is frequently characterized by macro-invertebrates, fish, or other invertebrates (Bradley et al., 2017).

Hydroecological models are predominantly developed through statistical methods such as regression analysis, including multiple linear regression (e.g., Clarke & Dunbar, 2005, and Monk et al., 2007), and multilevel models (recent examples include Bradley et al., 2017, and Chadd et al., 2017). Algorithms are commonly employed to do the "heavy lifting" in the determination of model structure; in hydroecology specifically, stepwise multiple regression is widely used.

Examples of the use of stepwise multiple regression in hydroecological modelling include Wood, Hannah, Agnew, and Petts (2001) for the identification of hydrological indicators of importance in a groundwater stream; Wood and Armitage (2004) to determine the influence of drought and low flow variability on macro-invertebrate abundance; Knight, Brian Gregory, and Wales (2008) to establish environmental flow requirements; Monk et al. (2007) and Worrall et al. (2014) on a Principal Component Analysis (PCA)-reduced set of hydrological indices; Surridge, Bizzi, and Castelletti (2014) included stepwise selection methods in their development of the iterative input variable selection algorithm (for the development of hydroecological models); Greenwood and Booker (2015) for the identification of important indices in the case of invertebrate response to floods; and Bradley et al. (2017) to realize important terms when considering the effects of groundwater abstraction and fine sediment pressures. Additionally, the authors have previously used a stepwise-based method as part of a preliminary analysis to identify a more complex aspect of the hydroecological relationship with regard to long-term flow variability and lag in ecological response (Visser et al., 2017). Nonstatistical hydroecological modelling is also known to make use of stepwise selection, for example, Parasiewicz et al. (2013) apply stepwise methods in their application of the MesoHABSIM model.

Stepwise methods are attractive, in general, as the statistical theory and assumptions are well established (Whittingham, Stephens, Bradbury, & Freckleton, 2006). Burnham and Anderson (2002) assert that they represent a particularly straightforward and accessible method for the nonstatistician. An algorithm adds and/or subtracts variables (indices) according to identified criteria, stopping once the criterion has been met, resulting in a single, final model. The assumption is that this single model represents the "best" model with the most predictive power.

Increasingly, there is widespread recognition of the limitations of stepwise methods, which have, in the past, been overlooked (Hurvich & Tsai, 1990; Steyerberg, Eijkemans, & Habbema, 1999; Whittingham et al., 2006). A model of a system is, by nature, only ever an approximation of reality; there is no such thing as a true model (Burnham & Anderson, 2002). Coupled with the increasing complexity of hydroecological modelling, the robustness and validity of the statistical approach is critical. In applied statistics, alternate modelling approaches are increasingly favoured, particularly in the ecological sciences (Burnham & Anderson, 2014; Hegyi & Garamszegi, 2011; Stephens, Buskirk, Hayward, & MartÍNez Del Rio, 2005; Wasserstein & Lazar, 2016; Whittingham et al., 2006). Alternate regression methodologies include partial least squares regression, an option when the predictors are not truly independent (common in hydroecological modelling); and shrinkage methods, where penalties/constraints are introduced; ridge and lasso regression can be effective when there are a large number of predictors (Dahlgren, 2010).

Since the beginning of the 21st century, three measures of statistical validity have been identified with unanimity across disciplines: effect size, levels of (statistical) uncertainty, and the weight of evidence supporting the hypothesis (Burnham & Anderson, 2002; Burnham, Anderson, & Huyvaert, 2011; Stephens et al., 2005; Wasserstein & Lazar, 2016; Whittingham et al., 2006). In asking what methods can satisfy these requirements, the field of information theory stands out as the dominant alternative (see position arguments and extensive discussion: Burnham et al., 2011 and Whittingham et al., 2006). Chadd et al. (2017) represents one of the few examples of the application of information theory in hydroecological modelling.

In this paper, the standard hydroecological approach for developing statistical models (stepwise selection) is compared with the increasingly popular information theory, now regularly utilized in applied ecology to investigate which is the most appropriate approach to model the complexities of the hydroecological relationship. Multiple regression models are developed for a groundwater-dominated catchment, where two scenarios of different levels of complexity are considered: The first features standard interannual variables, whereas the second considers lagged ecological response. The performance of each approach in each scenario is assessed.

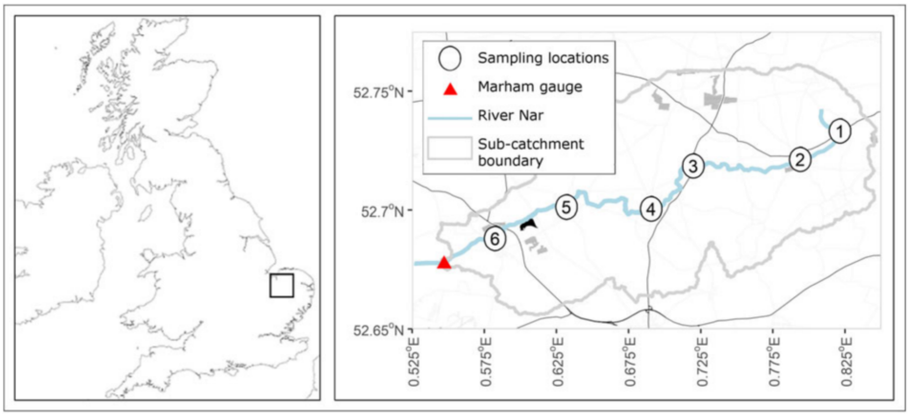

FIGURE 1 Left: Location of the River Nar. Right: chalk subcatchment [Colour figure can be viewed at wileyonlinelibrary.com]

2 | METHODS

Models are developed for the groundwater-fed River Nar (Norfolk, UK; Figure 1). All analysis is performed using R (Version 3.4.0), an open source software environment for statistical programming (R Core Team, 2017).

2.1 | Catchment data

The River Nar has a distinctive change at its midpoint, from chalk to fen river. The focus of this paper is the 153.3 km^2 chalk subcatchment (Figure 1). A reliance on groundwater and aquifer recharge (BFI 0.91) results in a highly seasonal flow regime (Sear, Newson, Old, & Hill, 2005). Aquifer recharge primarily occurs in the winter months, with a progressive rise in flow until March/April.

Daily mean flow data (1990–2014; Figure 2) was extracted from the National River Flow Archive for the Marham gauge (TF723119; Figure 1; NRFA, 2014). The derived hydrological indices describe the magnitude component of the flow regime: high/low flows (Q10/Q90), moderate high/low flows (Q25/Q75), and median flows (Q50). The hydrological indices are considered multiseasonally, with the hydrological year subdivided into the two standard hydrologic seasons, winter (October–March) and summer (April–September).

Macro-invertebrates serve as the proxy for ecological response. Response is determined using the Lotic-Invertebrate Index for Flow Evaluation (LIFE), accounting for macro-invertebrate flow velocity preferences (Extence, Balbi, & Chadd, 1999). Macro-invertebrate sampling data were provided by the Environment Agency for six sites (Figure 1; EA, 2016); the sampling methodology follows the Environment Agency's standard semi-quantitative protocol (see Murray-Bligh (1999). Seventy-two macro-invertebrate samples, collected in the spring season (April–June, 1993–2012), were used to determine LIFE scores at the species level; see Figure 2 for the average spring LIFE scores during the study period. The ecological data were paired with the antecedent seasonal hydrologic indices.

2.2 | Modelling scenarios

The multiple linear regression modelling approaches are applied to two scenarios. In scenario A, the 10 (interannual) hydrologic indices described previously are considered. Scenario B incorporates ecological lag in response, a reflection of the inherent complexity of the hydroecological relationship. Following Visser et al. (2017), 30 hydrologic indices result from the interannual indices being time-offset up to 2 years (t-2).

2.3 | Stepwise regression

Two methods of stepwise selection are applied, backwards and bidirectional. Being unidirectional, backwards represents greater economy, performing fewer steps to select the smallest model. The algorithms are specified to remove variables which are not significant (alpha threshold = 0.05) and hence presumed unimportant to the hydroecological relationship. Bidirectional stepwise selection is applied using the function `step`, from the base statistical package `stats`, whereas the backwards algorithm is applied using the `ols_step_backward` function from `olsrr`, a package for the development of ordinary least squares regression models (Hebbali, 2017). These methods yielded the same models, therefore no further differentiation is made.

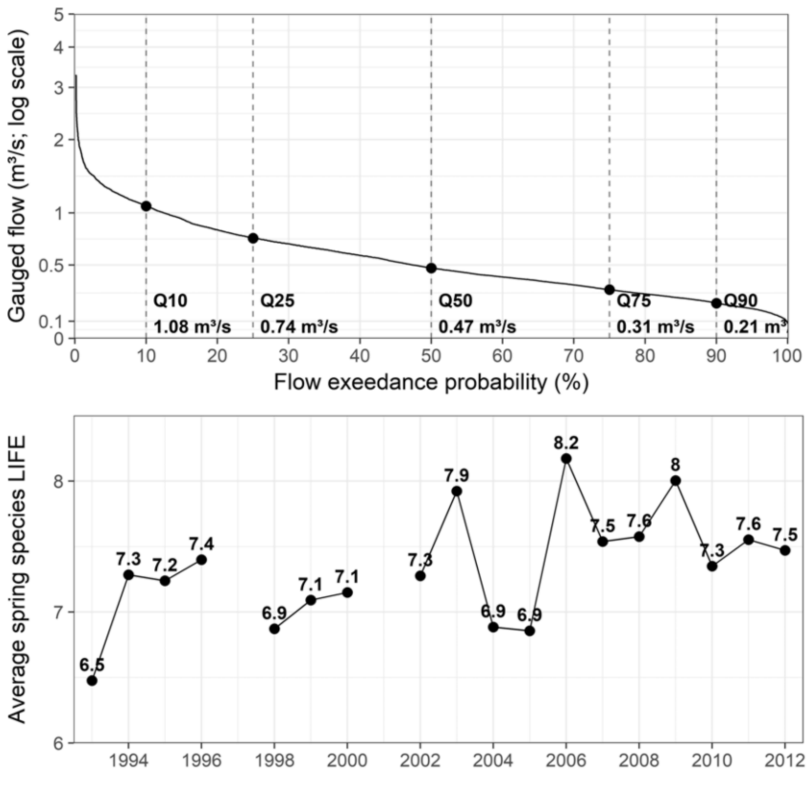

FIGURE 2 Flow duration curve (top) and average spring LIFE scores (bottom) during the study period

2.4 | Information theory

The information theory approach provides a quantitative measure of support for candidate models. Subsequently, inference is made from multiple models through model averaging. The candidate models are evaluated with respect to the three steps detailed below; for further information, see Burnham and Anderson (2002).

Step 1. Loss of information from model f

Kullback–Leibler measures the amount of information lost when model g is used to approximate reality, f. The model with the least information loss (greatest supporting evidence of the candidates) is considered the best approximation of reality.

The information loss, $I(f, g)$, is determined through computation of an information criterion. The Akaike Information Criterion (AIC) represents the standard estimate (Burnham & Anderson, 2002). In hydroecological modelling, the sample size is often small relative to the number of variables; here, a second order bias correction, AICc, is used (Burnham & Anderson, 2002).

Step 2. Evidence in support of model g_i

The value of AICc is dependent on the scale of the data; the goal is to achieve the smallest loss of information. This difference is rescaled and ranked relative to the minimum value of AICc:

$$\Delta_i = AIC_{ci} - AIC_{cmin} \; for \; i = 1, 2, \ldots, R. \tag{1}$$

This provides a measure of evidence, from which the *likelihood* that model g_i is the best approximating model can be determined. This is known as the Akaike weight, w, ranging from 1 to 0, for the most and least likely models, respectively:

$$w_i = \frac{\exp\left(-\frac{1}{2}\Delta_i\right)}{\sum_{r=1}^{R} \exp\left(-\frac{1}{2}\Delta_r\right)}. \tag{2}$$

Step 3. Multimodel inference

The best approximating model is inferred from a weighted combination of all the candidates. Parameter averages, $\hat{\hat{\theta}}$, are the sum of the Akaike weights for each model containing the predictor, $\hat{\theta}$:

$$\hat{\hat{\theta}} = \sum_{i=1}^{R} w_i \hat{\theta}_i. \tag{3}$$

Parameter averages are ranked, such that the highest value represents the most important in the model.

2.5 | Package glmulti

There are two options for the application of information theory in R: `MuMIn` (Bartoń, 2018) and `glmulti` (Calcagno, 2013). The application of the former centres around "dredging" (data mining) to determine the model subset (e.g., see Grueber, Nakagawa, Laws, and Jamieson (2011)). The package `glmulti` offers apposite functionality (see below) and has been developed and applied in a relevant discipline (see). In `glmulti`, information theory is applied to subsets of models selected by a genetic algorithm (GA) from which the multimodel average is derived using the function `coef`. A GA is a type of optimization that mimics biological evolution. The GA incorporates an immigration operator, allowing reconsideration of removed variables. Immigration increases the level of randomisation and hence the likelihood of model convergence on the global optima (the best models from the available data) rather than some local optima (Calcagno & de Mazancourt, 2010). Inference from a consensus of five replicate GA runs has been shown by Calcagno and de Mazancourt (2010) to greatly improve convergence.

2.6 | Analysis

For each scenario/approach, the best approximating model is derived. The comparative assessment looks at model structure, modelling error and statistical uncertainty.

The analysis of the model structures begins with a review of the selected indices and summary statistics (adjusted R-squared and *P* values). Being evidence-centric, these statistics are at odds with the underlying philosophies of information theory (revisited in the discussion). Instead, importance, the relative weight of evidence in support of each index in the model (Step 3), is considered.

Model error assesses how well the given model simulates the data, here, the observed data. Analysis centres on relative error, defined as the measure of error difference divided by observed value. These errors are presented as an observed-simulated plot. The distribution and magnitude of modelling errors is further considered through probability density functions.

Uncertainty is introduced throughout the modelling process. In this paper, the focus is on statistical uncertainty defined by Warmink et al. (2010, p.1520) as a measure of "the difference between a simulated value and an observation" and "the possible variation around the simulated and observed values," quantified as $1.96 \cdot \sqrt{variance}$, where 1.96 represents the 95% confidence level. Simply put the model with the least uncertainty, and hence, the most support should be the best representation of reality. In practice, statistical uncertainty dictates the usefulness of the model. Inaccurate appreciation of this uncertainty, however, prevents meaningful interpretation of the results, leading to less than optimal decision-making (Warmink et al., 2010).

The type of statistical uncertainty quoted is dependent on the modelling approach. For the stepwise approach, parameter (conditional) uncertainty, a measure of the parameter variance in the selected model, is provided. However, model selection represents a further source of statistical uncertainty (Anderson, 2007); when a model is derived from a single data set, there is a chance that other replicate data sets, of the same size and from the same process, would lead to the selection of different models. As a multimodel average, information theory provides a measure for this additional uncertainty, referred to herein as structural uncertainty.

A Monte Carlo approach (MC) is used to explore model parameter space (uncertainty at the 95% confidence interval represents the upper/lower bounds). Traditional MC methods suffer from clumping of points; this occurs because the points "know" (Caflisch, 1998) nothing about each other. To reduce the number of simulations required, a Quasi-MC method (Sobol-sequence) is applied, where elements are correlated and more uniformly well-distributed; 200 simulations appeared sufficient. The relative error distributions (based on the observed data) are again plotted. An extract of these plots, at the 5/50/95% densities illustrates the error distribution across the simulations.

3 | RESULTS

3.1 | Scenario A

3.1.1 | Model structure

The structure of the best approximating models is detailed in Table 1 and Figure 3 (facet 1). The information theory multimodel average, features five hydrologic indices, with a focus on low flows in summer and winter (Q_s90 and Q_w90). The stepwise selected model is similar, except here the Q_s90 index is not present, with this model favouring less extreme low flows (Q_s75).

Summary statistics for the two best approximating models are detailed in Table 1, with both achieving similar adjusted R-squared values. The *P* value, the principal selection characteristic in stepwise approaches, is distinctly lower in the information theory model. The second and third best-performing stepwise selection models saw the removal of the Q_s25 index, and then Q_s10 in the final step. These models have a similar fit to the selected model, with adjusted R-squared values of 0.52 and 0.55, respectively. For the information theory model, an estimate of the relative weight of evidence in support of each index (Figure 3, facet 1) suggests that the winter hydrologic indices are the most meaningful.

3.1.2 | Model error

Modelling errors are presented in Figure 4. Overall, there appear to be minimal differences between the two approaches, with the stepwise selected model featuring marginally less error. In Figure 4a, it can be seen that the models perform slightly worse at the extremes, with the stepwise model achieving a slightly better fit overall. This is further evidenced in Figure 4b, where errors can be seen to concentrate on the left. Finally, the fitted distributions in Figure 4c feature considerable overlap, further emphasizing the similarities in model performance.

3.1.3 | Model uncertainty

The statistical uncertainty, relative to the parameter estimate, is summarized in Figure 5 (facet 1); the stepwise selected model

TABLE 1 Model structures and summary statistics

Scenario	Approach	Model	Adj. R^2	*P*
A	Stepwise selection	$\text{LIFE} = -3.50Q_s50 + 5.45Q_s75 - 1.42Q_w75 + 3.60Q_w90 + 6.39$	0.4	0.004
A	Information theory	$\text{LIFE} = -1.54Q_s50 + 1.46Q_s75 + 1.68Q_s90 - 1.13Q_w75 + 3.25Q_w90 + 6.50$	0.41	0.003
B	Stepwise selection	$\text{LIFE} = -4.67Q_s^t50 + 6.71Q_s^t75 - 2.52Q_s^{t-1}50 + 5.43Q_s^{t-1}90 + 6.62$	0.41	0.003
B	Information theory	$\text{LIFE} = -0.88Q_s^t50 + 2.57Q_s^t90 - 1.29Q_w^t75 + 2.90Q_w^t90 + 0.56Q_w^{t-2}10 + 6.34$	0.47	0.002

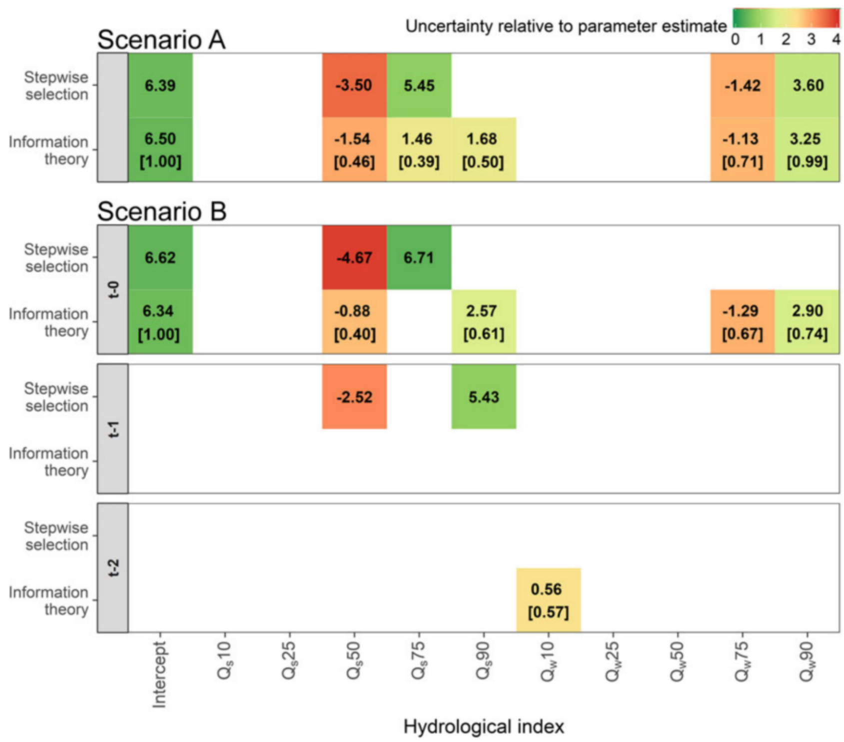

FIGURE 3 Model structure and estimates of parameter coefficients. Text overlays indicate the estimate, and for information theory, parameter importance (square brackets). For scenario B, each facet indicates a time-offset [Colour figure can be viewed at wileyonlinelibrary.com]

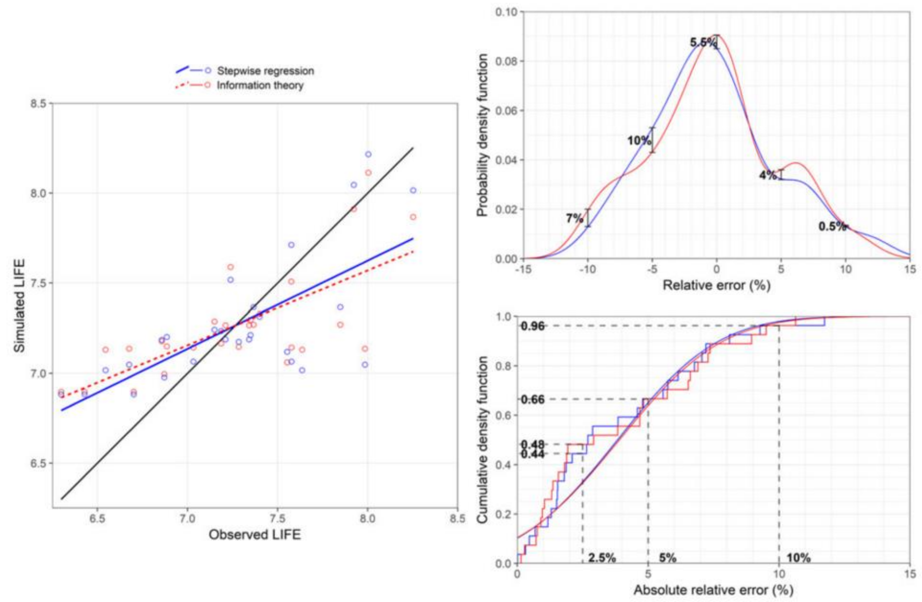

FIGURE 4 Scenario A modelling error. Observed simulated LIFE scores (left); probability density functions (fitted to a normal distribution) of relative error (top right); absolute relative error cumulative density functions (bottom right) [Colour figure can be viewed at wileyonlinelibrary.com]

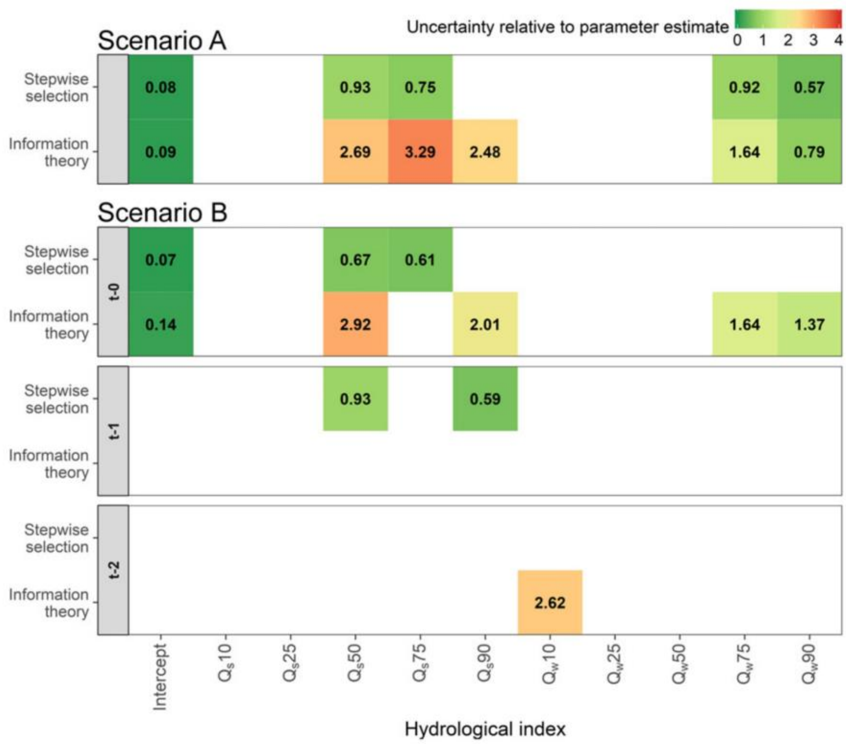

FIGURE 5 Uncertainty (95% confidence interval) relative to parameter estimates. For scenario B, each facet indicates a time-offset [Colour figure can be viewed at wileyonlinelibrary.com]

displays the least uncertainty. Differences are most notable in hydrological summer, suggesting greater confidence in the winter indices; this is in agreement with the information theory importance statistic.

Further inference regarding the implications of statistical uncertainty is made through the consideration of MC simulations (Figure 6). The cumulative density function (fitted to a normal distribution; Figure 6a,b) for each simulation provides an overview of the errors. This is further clarified in Figure 6c), where the errors at cumulative densities of 5/50/95% indicate the distribution of error across the simulations. For 5% of the data, the majority of the simulations feature 2.5% absolute error or less; this represents approximately 9% (stepwise) and 16% (information theory) of the simulations. At 50/95, the errors are similarly spread; the majority of stepwise models have approximately 20% error, whereas for information theory, this is 27.5%.

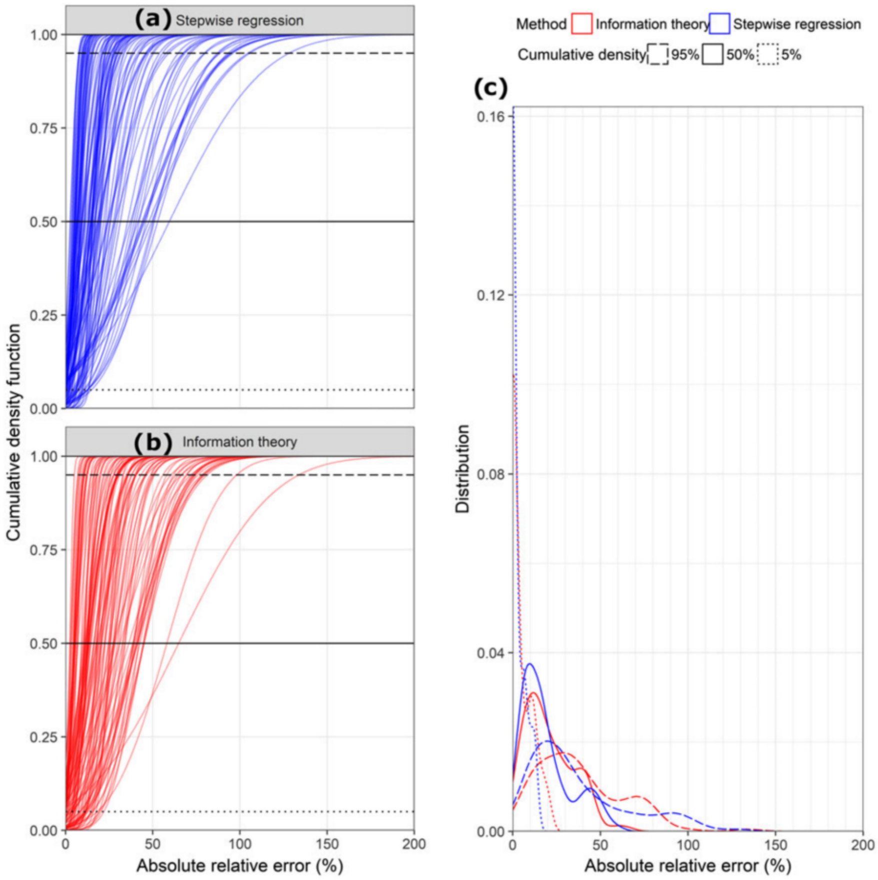

FIGURE 6 Scenario A, distribution of modelling errors following MC simulation. (a,b) Cumulative density function of the absolute relative error per simulation (fitted to a normal distribution); (c) distribution of the absolute relative error for 5/50/95% of the data [Colour figure can be viewed at wileyonlinelibrary.com]

3.2 | Scenario B

3.2.1 | Model structure

Here, the differences between model structures are greater than Scenario A (Table 1 and Figure 3, facets 2–4). The stepwise selected model incorporates two nonlagged and two lagged indices. The two nonlagged parameters represent summer median and moderate low flows (Q_s50 and Q_s75). The large coefficients of these two parameters suggests a preference for mid range flows which are not too low or high; in this, the scenario B model is broadly consistent with scenario A. However, the model takes no account of winter flows. In contrast, the information theory model structures (and measures of parameter importance) for both scenarios are similar, with the only difference being the inclusion of lagged winter high flow (t-2). Physically, this could represent the time delay of the groundwater recharge. There is no acknowledgement of this phenomenon in the stepwise selected model, whether subject to lag or otherwise. In this scenario, the summary statistics (Table 1, rows 3 and 4) associated with the stepwise model remain relatively static. However, the adjusted R-squared for the information theory model is 14% greater than the stepwise model.

Overall, the information theory model indicates a preference for variability in flow magnitude, possibly a reflection of the seasonal nature of the flow regime. Winter flows stand out as the most important facet of the flow regime. In contrast, the stepwise selected model suggests a preference for more uniform flows (that are not too low); unusually, winter flows are considered unimportant.

3.2.2 | Model error

The errors associated with each model are detailed in Figure 7. At first glance, Figure 7a suggests that the models perform equally well for lower LIFE scores, whereas for higher values the information theory model provides marginally better estimates. This is reinforced in Figure 7b, where the relative errors are centred around 0% and −4% for the information theory and stepwise models, respectively. The stepwise model also has a tendency to overestimate.

The extent of these differences is evident in Figure 7c. For the information theory model, 56% of the estimated data points have 5% or less absolute relative error, in fact, almost 50% of the data has less than 2.5%. This is in direct contrast to the stepwise selected model, where only 15% of the data has less than 2.5% absolute relative error; this increases to approximately 48% at 5%. The models do not converge until approximately 9.25% absolute relative error, that is, the largest errors for both models are comparable.

3.2.3 | Model uncertainty

Relative to scenario A, these is an increase in the range of statistical uncertainty (Figure 5, facets 2–4), particularly for the information

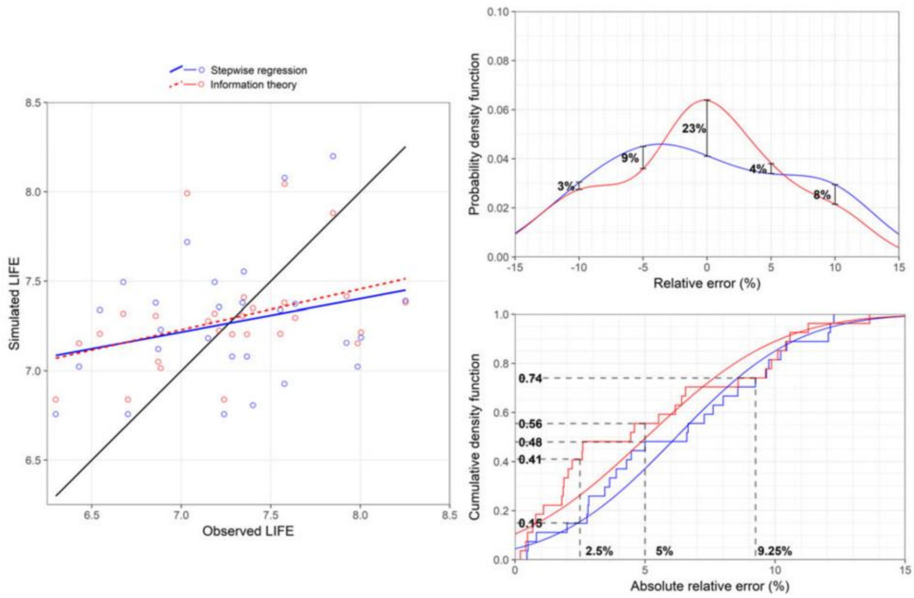

FIGURE 7 Scenario B modelling error. Observed simulated LIFE scores (left); probability density functions (fitted to a normal distribution) of relative error (top right); absolute relative error cumulative density functions (bottom right) [Colour figure can be viewed at wileyonlinelibrary.com]

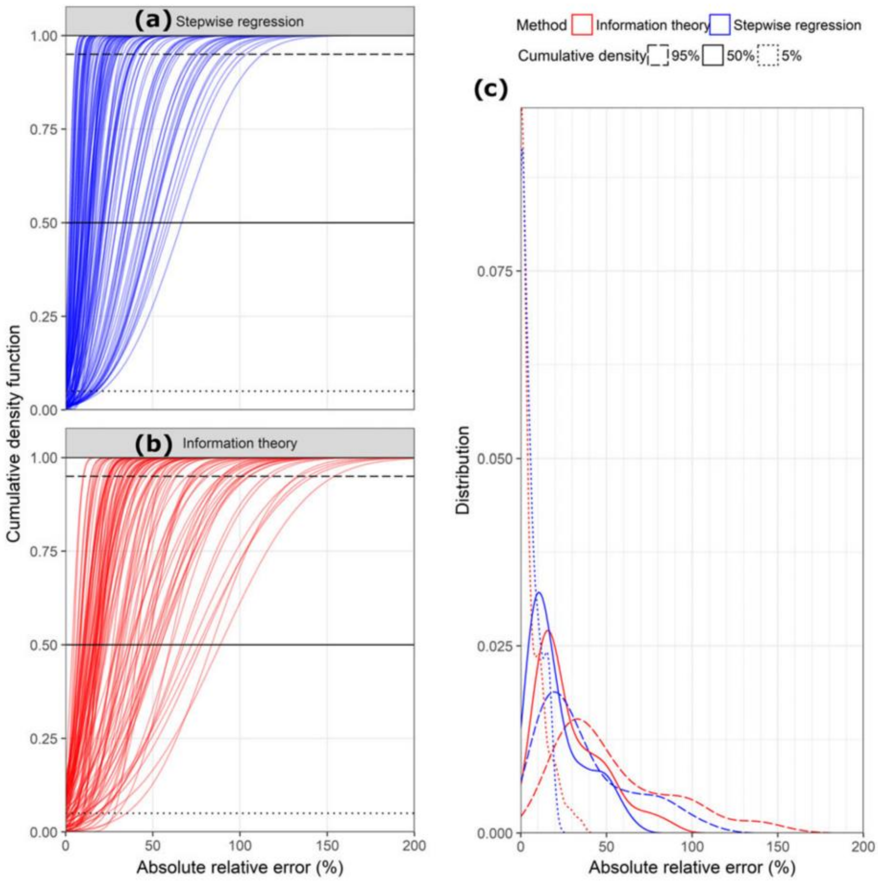

FIGURE 8 Scenario B, distribution of modelling errors following MC simulation. (a,b**)** Cumulative density function of the absolute relative error per simulation (fitted to a normal distribution); (c) distribution of the absolute relative error for 5/50/95% of the data [Colour figure can be viewed at wileyonlinelibrary.com]

theory model. Figure 8a,b shows the information theory MC simulations to be more widely distributed than the stepwise. A snapshot of the error distributions at cumulative densities of 5/50/95% is shown in Figure 8c. It is noteworthy that, here, the range of densities on the y-axis is narrower than in scenario A. The difference is more marked at the 50% and 95% densities, where the distribution of the information theory simulations is flatter and wider, indicating a greater spread of error; in contrast, the error in the stepwise simulations tends towards the lower end.

4 | DISCUSSION

The initial focus herein is model inference and consideration of the explicit implications of the results. To gain further information on the relative strengths and weaknesses of the two approaches, it is necessary to look beneath the surface. The statistical robustness of the models produced is considered, as well as the underlying philosophies of each approach.

4.1 | Model inference

In scenario A, the principle difference in model structure is the parameterisation of summer low flows; information theory focuses on low flows (Q_s90) rather than moderate low flows (Q_s75). Consequently, the differences in modelling error is small. Consideration of statistical uncertainty and the error distributions reveals the stepwise selected model to be more balanced in terms of error distribution.

Despite demonstrated importance, as a groundwater-fed river (Sear et al., 2005), aquifer recharge is not recognized under the scenario B stepwise selected model. There is no consideration of hydrological winter and a low number of parameters overall; concerns thus emerge over the parameterisation of the stepwise selected model in this more complex scenario. In contrast, the information theory model includes seven hydrological indices, three of which reflect winter flows. The importance of these indices is further emphasized by the relatively high weight of evidence (Figure 3, facets 2–4).

Given the difference in model structure, the similarities in modelling errors are unexpected. Interestingly, with the information theory model, the shape of the error distributions is consistent across the two scenarios, it is only the magnitude of the error that varies (increasing in the lagged scenario). In contrast, the stepwise selected approach sees an increase in error.

The increased uncertainty in scenario B can be considered a direct consequence of the increased modelling complexity. Figure 5 (facets 2–4) suggests that the stepwise model is subject to less uncertainty. However, the MC simulations (Figure 8) show that the associated error distributions are similar with regard to shape. However, the information theory curve is slightly flatter, leading to errors of higher magnitude.

Based on these findings, it could be concluded that these two hydroecological modelling approaches perform at similar levels. The principal area for concern may be the increase in statistical uncertainty for the information theory model in the lagged scenario. However, it should be noted that the reasons for the increased uncertainty are multifaceted, a matter discussed further below. Despite differences in model structure and statistical uncertainty, all models, and hence both approaches, have been able to provide satisfactory predictions with comparable modelling error.

4.2 | Philosophical underpinnings

Looking to the statistical robustness of the approaches, and underlying philosophies, may serve to further elucidate which method is most appropriate in the hydroecological setting. Considered herein are model selection, the definition of evidence, and statistical uncertainty.

4.2.1 | Model selection

In scenario A, the stepwise model was selected following six steps, that is, six hydroecological models were considered. In terms of their summary statistics, the models considered in the fourth and fifth steps are remarkably similar to the selected model; despite this, under this methodology, these models are rejected. Consequently, in the baseline scenario, hydrological indices capturing summer high flows (Q_s10 and Q_s25) were rejected as model parameters. It could be argued that, by simply making this observation, that this is an elementary form of multimodel inference. In practice, however, these second and third ranking models would not be subject to analysis, and thus, such information would be left unknown. Consequently, it is inferred that the selected model is the only model fit (Burnham & Anderson, 2002). In the alternate approach, information theory considers a larger candidate set, the result being a model-average. Consequently, important variables have not been subject to rejection. This is reinforced by the index of importance (Figure 3), an indication of the relative "importance" of each parameter. By calculating and reporting this statistic, it is evident that the variables incorporated in the model are those which are most supported by the data. Consequently, more conclusive statements may be made with regard to the model. For example, in scenario A, it would not be incorrect to state that, given the data, low flows are more important than high flows in the hydroecological relationship for this case study river. Such conclusions would be pure conjecture in the case of the stepwise selected model.

4.2.2 | Evidence

The use of *P* values has been subject to considerable criticism in excess of 80 years (Burnham & Anderson, 2002). In the context of hydroecological modelling, the fundamental problem is with misinterpretation, where *P* values are interpreted as evidential. In a statistical sense, the *P* value is a measure of the probability that the effect seen is a product of random chance. Probability is a measure of uncertainty, not a measure of strength of evidence, which is based on likelihood. (Burnham & Anderson, 2002).

This misinterpretation is not exclusive to hydroecological modelling or stepwise selection, it is prevalent in academia (for example, see Wasserstein and Lazar (2016)). As such, this is such an ingrained error that it cannot be viewed as a criticism of the hydroecological modeller. In their paper on the development of the LIFE hydroecological index (Extence et al., 1999, p. 558), the authors fall into this trap:

> *"At Brigsley on the Waithe Beck, for example, there are 177 separate correlation coefficients significant at* p < 0.001, *13 at* p < 0.005, *six at* p < 0.01, *ten at* p < 0.05 *and eight correlations that are non-significant, for the period 1986–1997. From this surfeit of usable statistics, those flow variables showing the best relationships with the invertebrate fauna are proposed as being of primary importance in determining community structure in particular river systems."*

Here, the authors interpreted the *P* value as a weight of evidence, assuming that those 177 models with the lowest *P* values were "best." Such explicit use of *P* values is no longer commonplace; however, the stopping rule applied in stepwise selection does utilize *P* values in precisely this manner, a practice which is described by Burnham and Anderson (2002, p.627) as "perhaps the worst" application of *P* values.

The misunderstanding of the definition and purpose of the *P* value raises concerns with its use in hydroecological modelling. Questions are therefore raised over the statistical robustness, or accuracy, in the application of stepwise methods, and thus, its ability to recognize the inherent complexities of the hydroecological relationship, as well as the selection of the final model. In this case, it could be argued that as an evidence-based methodology, information theory offers clearer, more robust statistical inference. Indeed, this is recognized by two of the authors of the 1999 LIFE paper, who have recently looked to information theory when developing and applying a new index, the Drought Effect of Habitat Loss on Invertebrates (DELHI; Chadd et al. (2017)).

4.2.3 | Statistical uncertainty

Statistical uncertainty is the principal determinant of the usefulness and validity of a model. As suggested previously, given the lower uncertainty, it might be concluded that the stepwise approach performs better overall, particularly in the case of the more complex scenario B, where the uncertainty increases further. However, as discussed under methods, these two modelling approaches report different statistical uncertainties. The stepwise model considers parameter uncertainty, whereas the information theory model also quantifies error due to model selection, thereby providing a measure of the overall structural uncertainty. The subsequent higher uncertainty simply represents a more realistic measure, as Anderson, 2007 (p. 113) points out, when only parameter uncertainty is considered, the "confidence intervals are too narrow and achieved coverage will often be substantially less than the nominal level (e.g., 95%)."

5 | CONCLUSION

As further aspects of hydroecological relationships are understood, such as ecological lag in response, the likelihood of modelling errors and statistical uncertainty is increased, commensurate with the additional complexity. It is thus vital to ensure the modelling approach is suitably robust. Here, the performance of stepwise selection, one of the standard hydroecological approaches, is considered alongside an alternative popular in applied statistics, information theory. The best approximating models are analysed comparatively. The approaches are applied to two scenarios with increasing complexity: scenario A, focussing on standard interannual variables, and scenario B, taking into account any effect of lag in ecological response.

Notable differences in the models are confined to the lagged scenario. Of foremost concern is the structure of the stepwise selected model. Aquifer recharge is fundamental to flow in groundwater-fed rivers, which is a feature of the case study river examined. In this paper, this physical property is assumed to be represented by the winter variables. In scenario A, this is accounted for through two winter low flow variables, Q_w75 and Q_w90. This is repeated in scenario B for the information theory model, plus an additional lagged high flow variable. Despite their recognized importance, the stepwise selected model includes no winter variables, leading to concerns over its ability to capture the essential physical processes in such complex scenarios.

In terms of model performance, the information theory approach resulted in fewer modelling errors but in greater statistical uncertainty. Despite this, the measure of uncertainty provided by stepwise selection is considered an underestimate (Burnham & Anderson, 2002) as the variance due to model selection is not incorporated; the estimate considers only parameter variance. It may seem contradictory to say that the model subject to greater uncertainty provides the better measure; however, the stepwise selected model inherently suffers from confidence intervals which are too narrow, with the achieved coverage being less than the standard, nominal 95% (Anderson, 2007).

From a utilitarian perspective, one might say that no approach has been demonstrated to be categorically better than the other. However, modelling is only ever an approximation of reality, and the best, true model remains an unknown. Still, in approaching the truth, we must have some criteria to adjudge success, and here, these have been identified as approaches which focus on effect size, statistical uncertainty, and the weight of evidence. Based on the results presented here, information theory satisfies these three best. In contrast, stepwise selection offers a *P* value, an arbitrary probability measure, which is not a measure of effect size. The uncertainty it measures is an underestimate and weight of evidence is not possible under this approach.

Finally, though no approach emerged a clear "winner," the information theory model still performed empirically better in the two scenarios considered. It presented significantly fewer modelling errors, and although the measure of statistical uncertainty is larger, and thus inconvenient, it may also be viewed as a truer representation of a complex reality, than that provided by its stepwise counterpart.

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How to cite this article: Visser AG, Beevers L, Patidar S. Complexity in hydroecological modelling: A comparison of stepwise selection and information theory. *River Res Applic*. 2018;1–12. https://doi.org/10.1002/rra.3328

6. AFTERWORD TO PUBLICATION 2

This second publication set out to highlight the weaknesses (statistically) of the traditional stepwise approach to hydroecological modelling, based on evidence from literature, and through practical examples. Comparison of this traditional approach with information theory, through their application within the principal case study, illustrated an alternative, and apparently more robust method. Models were developed for two scenarios of increasing complexity; the first considered inter-annual hydrological indicators (immediately preceding flow only) whilst the second saw the consideration of time-offset hydrological indicators to account for lag in hydroecological response.

In the first scenario (no time-offset), limited differences in model structure and performance were observed, thereby suggesting that stepwise selection performs adequately, at least in simpler cases. In the second scenario (with time-offset) there was less agreement. In terms of model structure, the stepwise model did not see the selection of any winter hydrological indices. As the principal case study is a groundwater-fed river, with aquifer recharge occurring in the winter months, this model is unlikely to be an accurate representation of reality. The problem of equifinality is thus highlighted; if the focus were not on a single best model, critical winter hydrological indicators would likely have been present in the model. Conversely, the information theory multi-model average included three winter indices, one of which was time-offset.

Modelling error and uncertainty were shown to increase with the level of complexity. In the second scenario, the model derived following the information theory approach exhibited less model error than the stepwise selected model. Despite this, the model had higher associated uncertainty. This was put into context through consideration of the literature: stepwise selection is known to underestimate uncertainty, focussing only on the uncertainty associated with parameter variance, thereby increasing the risk of erroneous conclusions (Whittingham *et al.*, 2006; Wasserstein and Lazar, 2016). Further, Grueber *et al*. (2011) observe that if one model is clearly superior to the rest, it is reasonable to use that model for prediction, but its uncertainty should be evaluated using the entire set of candidate models. If one model is not clearly superior, then it is reasonable to weight all predictions. This philosophy is conspicuous by its absence under the stepwise protocol.

By contrast, the information theory approach, combined with the multi-model average, is able to consider both parameter and structural uncertainty. Overall, the information theory approach is shown to reduce modelling error whilst also providing a more realistic representation of modelling uncertainty.

Model performance was similar for both modelling approaches, with the principal difference being in the measurement of uncertainty. Uncertainty, as measured by information theory, encompasses significantly greater information, and thereby provides a more realistic measure. It is concluded that the information theory approach is more accurately reflective of the complexity found in real-world applications.

The publication does not, and did not intend to, seek to resolve all the issues relating to sound statistical practice in hydroecological modelling. Instead, it promotes the case for better, or best, statistical practice. The author fully acknowledges that both methods are vulnerable to misuse, and care must be taken in the use of either approach by users (Stephens *et al.*, 2005). Nevertheless, information theory is clearly superior to the traditional stepwise approach in terms of potential statistical robustness. In light of the findings in publication 2, the author is in absolute agreement with Whittingham *et al.* (2006) who consider stepwise multiple regression to be *"bad practice".*

7. VALIDATION

The focus of this chapter is the refinement and optimisation of current hydroecological modelling practice. Subsequently, the derived methodology will form stage 1 of the wider coupled modelling framework. Publication 1 provided mathematical confirmation of delays in ecological response beyond the immediately preceding flow (within 6-12 months). The second publication identified information theory as a statistically robust alternative to stepwise selection, minimising both model error and enabling holistic quantification of uncertainty. Serving to provide a proof of concept, both publications were focussed on the principal case study. This section looks to establish the validity and wider applicability of this optimisation. This is achieved through:

(1) Consideration of a suite of 84 ecologically relevant hydrological indicators (ER HIs) (*Appendix A*, Table A-4), capturing the range of variability;

(2) Application to five hydrologically diverse case studies, including the principal, River Nar. For further details, see *Chapter 2. Case study catchments*.

The refined methodology is first introduced alongside an overview of the data available for each case study. In *7.2 Results*, the performance of the hydroecological models is assessed; a brief discussion follows.

7.1 METHOD

Figure 3-3 provides an overview of the refined hydroecological modelling framework, as applied to the five case study catchments. In brief, time series of daily gauged flow, from the National River Flow Archive, are used to determine a suite of ER HIs, capturing the five facets of the flow regime (for details, see *Appendix A*, Table A-4). These indicators are offset, from *t-0* to *t-n*, leading to an n-fold increase in the number of ER HIs; n is determined by data availability. Long-term macroinvertebrate records are used to determine the response variable, LIFE (Extence *et al.*, 1999), the proxy for river health. The response and predictor variables are paired, with the number of ER HIs subsequently reduced through the application of PCA. The hydroecological model, in the form of a multi-model average, is then determined through application of information theory, as described in publication 2.

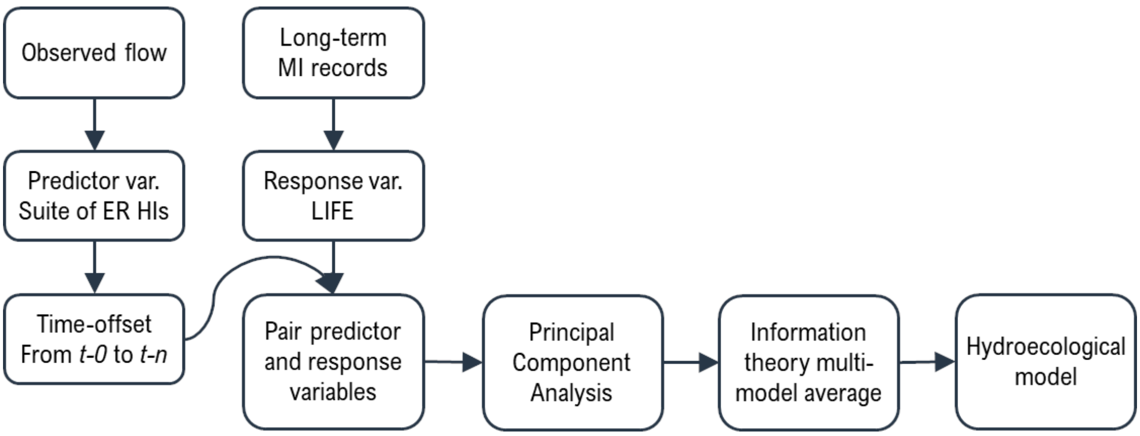

Figure 3-3. The refined hydroecological modelling framework, representing stage 1 of the coupled modelling framework. *Source: Annie Visser-Quinn.*

For data availability, see Table 2-1. With a considerably higher number of ecological samples, collected over 20 distinct spring seasons, a time-offset of up to 2-years was considered for the principal case study, the River Nar; for the additional case studies, a maximum time-offset of 1-year was applied.

7.2 RESULTS

The underlying hydroecological processes are first considered, with reference to the facets of the flow regime captured by each model. These results are aggregated, in order to better enable comparison across the case studies. The focus here lies upon validation, and demonstration, of the modelling framework. Ancillary detail, in the form of the hydroecological models and descriptions of the ER HIs, is provided in Appendix A. Following the analysis made in publication 2, *section 7.2.2* provides a review of the predictive ability and parameter uncertainty associated with each model.

7.2.1 Underlying hydroecological processes, by facet of the flow regime

In Figure 3-4, indicator importance is aggregated by facet of the flow regime, where importance represents the relative weight of evidence in support of the inclusion of the indicator in the hydroecological model. For example, for the Tarland Burn, the lagged winter indicators capturing the interquartile range (IQR) and quantile ratios (Q80Q50 and Q90Q50) represent average flows under the magnitude facet (x-axis, M-A).

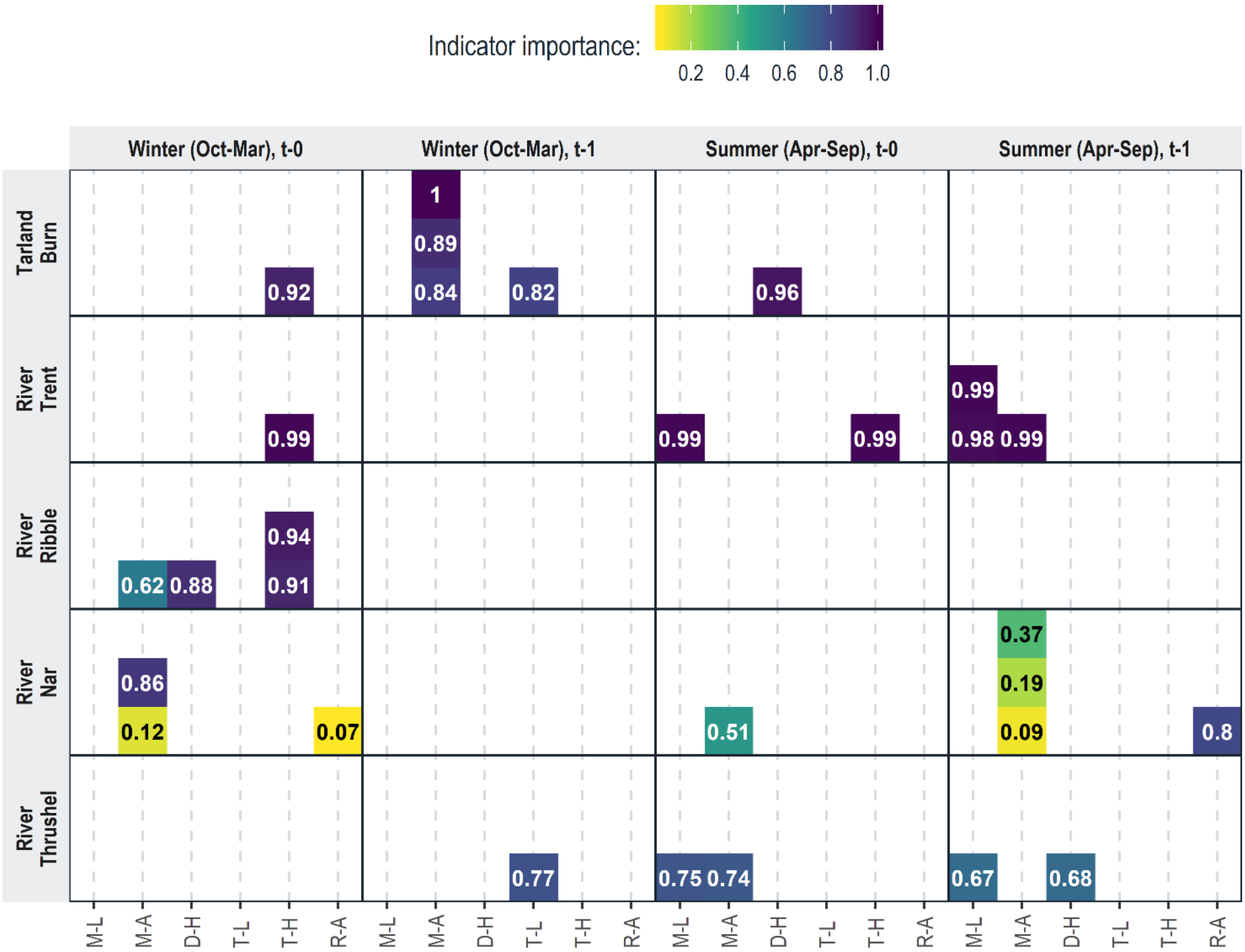

Figure 3-4. Aggregation of the ER HIs by season, time-offset, and facet. The colour-scale and numbers represent the importance of each ER HI. On the x-axis, the first letter represents the facet of the flow regime (magnitude, M; duration, D; timing, T; and rate of change, R), whilst the second specifies the aspect, low (L), average (A) or high (H) flows. *Source: Annie Visser-Quinn.*

Looking to the second and fourth columns, it can be seen that just under half of the indicators are time-offset (n = 14). The majority of these capture summer flows, suggesting that delays in ecological response predominantly occur as a result of flows in hydrological summer. With regards to the facets of the flow regime, the majority of indicators (n = 15) represent flow magnitude. For four out of five catchments, the timing of flows in hydrological winter is indicated as being of particular import.

The distribution of indicators across seasons, time-offsets and facets highlights the hydrological diversity of the case studies. A review of the dominant organising factors, with reference to Figure 3-4, follows for each case study.

- *Tarland Burn.* The Tarland Burn represents the only Scottish case study. The presence of bogs in this catchment results in a higher Baseflow Index (BFI) (the proportion of flow derived from stored sources, e.g. groundwater) than might be expected in a catchment with an igneous bedrock geology. All six ER HIs have a high importance, indicative of a high level of support (information) for their inclusion in the model. The model structure (Appendix A, Table A-5) reveals that ecological health is dependent upon a balance of the magnitude and timing of winter high and low flows; a delay in ecological response to these flows is indicated through the time-offset. One reason for this dominance of winter flows may be the increased runoff which occurs when bog is saturated. The effect of these winter flows is balanced by the duration of high flows in hydrological summer;
- *River Trent.* All six of the indicators are of almost equal importance, with summer flows having the greatest influence (five out of six indicators). Timing is of particular import, with the same index captured in winter as in summer. Two of the magnitude indices also capture an element of time (Table A-5), representing monthly averages and variability. The negative signs of two of the three time-offset indicators suggest that lag has a negative impact upon ecological health. This sensitivity to summer flows is consistent with Figure 2-4, where flow is shown to increase at a steady rate (limited variability) following the day of minimum flow;
- *River Ribble.* With a BFI of 0.25, surface runoff is the dominant controlling factor for this case study. The indicators reflect this, lag does not feature (fast response), whilst only winter flows are identified as important (when surface runoff, and hence flow, is highest). The instream ecology is particularly sensitive to the timing of maximum flows (negative impact), whereas the duration of high flow pulses, above a long-term winter Q25 threshold, has a positive impact on ecological health;
- *River Nar.* The principal case study. Additional analysis of this hydroecological model features in publication 4 *(Chapter 5. Coupled modelling framework)*. Relative to the other case studies, indicator importance is more variable. This could be a reflection of the complexity of the hydroecological processes in this catchment (groundwater-fed, high BFI of 0.91). The dominant organising factor is the lagged winter index capturing average flows. This level of influence, coupled with the associated lag, is consistent with the understanding of the importance of aquifer recharge over hydrological winter;

- *River Thrushel.* Structural uncertainty may be higher for this model due to the lack of any high importance indicators. A sensitivity to low flows is suggested by the dominance of low and average flow indicators. Notably, all but one indicator has a negative impact upon the ecological health of the river; only high minimum flows lead to an increase in LIFE. These observations appear consistent with Figure 2-4, where summer flows are regularly close to zero and the median flow, on the day of minimum flow, is just 0.15 mm/day.

7.2.2 Model predictive ability

The predictive ability of each model is assessed through a comparative assessment of the model error (how well the model simulates the observed data) (Figure 3-5). (As detailed in Section 4.2.1, this application of information theory assumes that errors are normally distributed. Figure 3-5 confirms this assumption. Note, it is assumed that the small 'humps' in the distribution are an artifact of the small sample size.) As in publication 2, the focus is on relative error, defined as the difference in the values divided by the observed value. A review of performance within each case study follows:

- *Tarland Burn.* Looking to Figure 3-5a, a lack of variability in observed LIFE score is in evidence. It is perhaps unsurprising that, given the limited number of data points, the model is not capable of picking up these more subtle changes. Consequently, in Figure 3-5b and c it can be seen that the Tarland Burn has the highest relative and absolute relative error of the case studies. However, with a maximum error of ±25%, the model remains usable;
- *River Trent.* This model tends to overestimate, particularly as LIFE score increases (Figure 3-5a). This is also reflected in the high range of error (relative to the other case studies) in Figure 3-5c;
- *River Ribble.* From Figure 3-5a, it can be seen that this is the only model where the simulated values do not positively correlate with the observations. The 'flatness' of the PDF in Figure 3-5b is a reflection of the wide range of error;
- *River Nar.* Of the case studies, the River Nar simulations follow the 1:1 line most closely (Figure 3-5a). This level of performance is reflected across Figure 3-5b and

c, with both error distributions centred around zero. A minor negative bias (tendency to underestimate) is in evidence;

- *River Thrushel.* Model performance is similar to the River Nar, although with a slightly larger negative bias (Figure 3-5b).

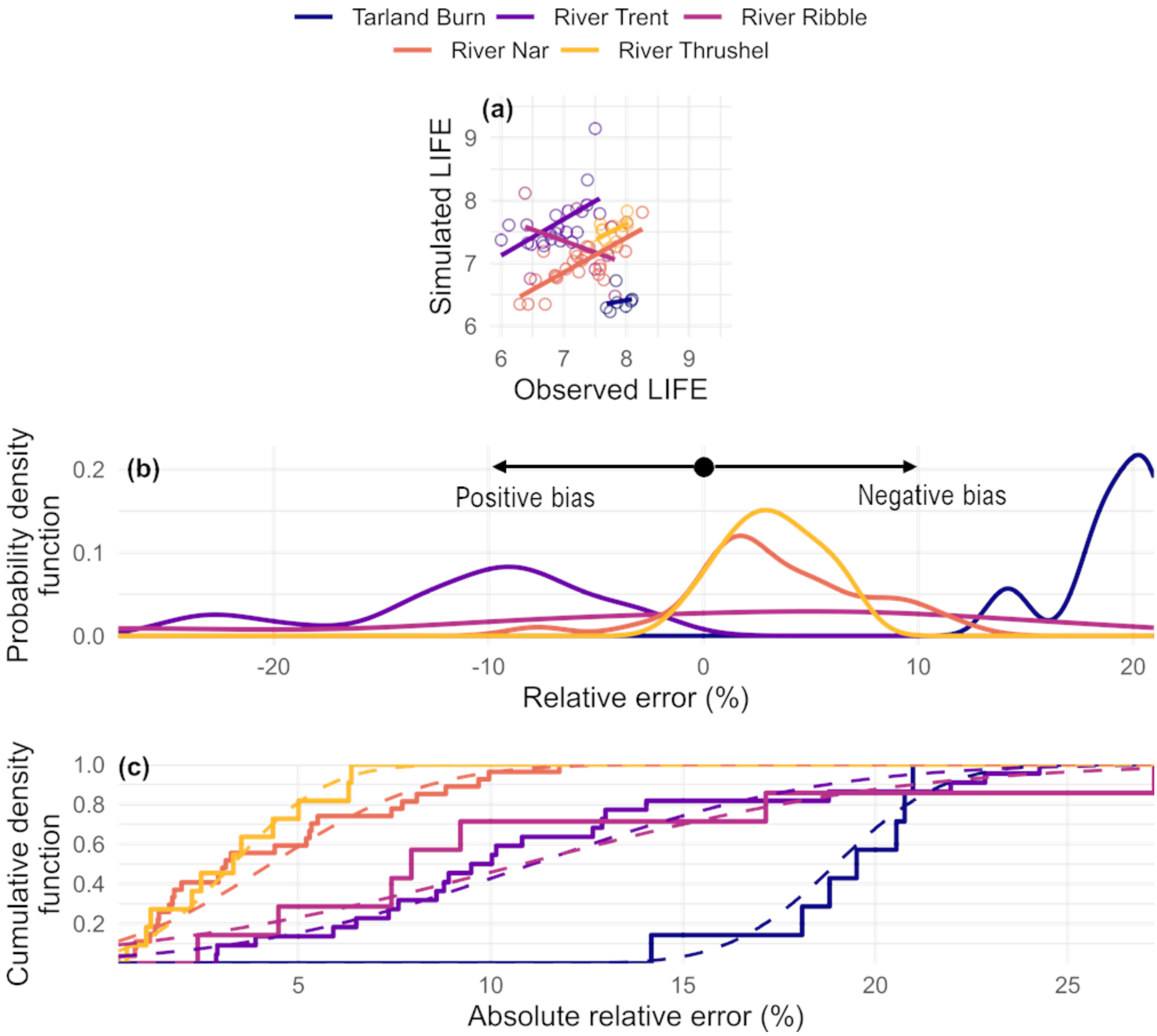

Figure 3.5. Comparison of modelling error across the case study catchments. The three panels represent: *(a)* Observed-simulated LIFE scores; *(b)* probability density functions (PDF) of percentage relative error; and *(c)*, cumulative density functions (CDF) of the absolute relative error. In (c) the CDF fitted to a normal distribution is overlain. *Source: Annie Visser-Quinn.*

7.2.3 Parameter uncertainty

As in publication 2, the impact of parameter uncertainty is assessed through consideration of Monte Carlo simulations (Figure 3-6); here, n = 10,000. Due to the limited number of data points, it was not possible to estimate parameter uncertainty for the Tarland Burn and River Trent.

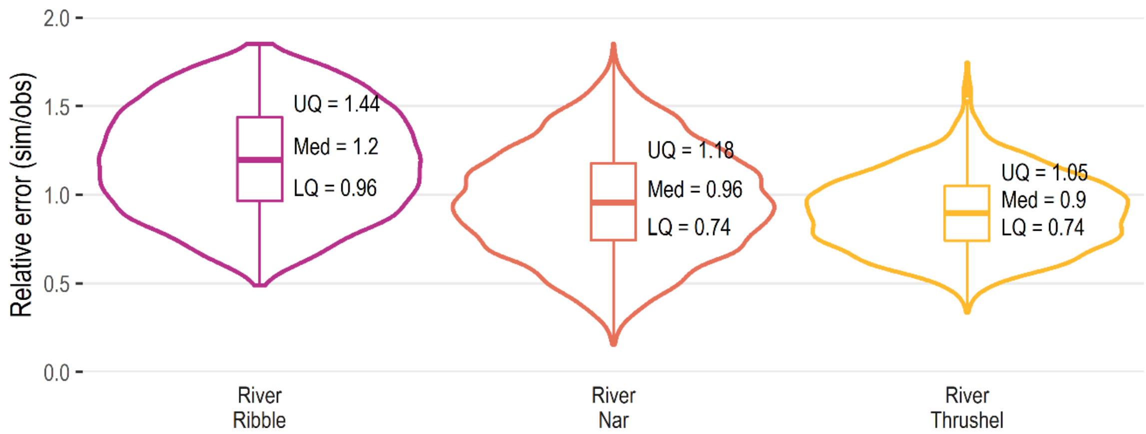

Figure 3-6. Hydroecological model parameter uncertainty (across the three case study catchments with sufficient data availability); distribution of the relative error for 10,000 MC simulations. *Source: Annie Visser-Quinn.*

Of the three remaining case studies, the parameter uncertainty for the River Ribble is highest, with an interquartile range of 0.48. For the River Thrushel, there is a slight negative bias, however the interquartile range is the lowest at 0.31. The principal case study has a higher interquartile range of 0.44; however, here relative error centres around one (perfect agreement). Overall, parameter uncertainty is sufficiently minimal and consistent to be considered acceptable.

7.3 DISCUSSION

In order to assess the validity of the hydroecological modelling approach it is first necessary to determine whether the ER HIs are consistent with the understanding of the catchment hydrological processes. The results presented suggest that this is the case; this appears to hold true irrespective of structural uncertainty or model error.

Consistency in performance across a range of hydrologically diverse catchments is a further requirement. Error in the predictive ability of the models was subject to variation across the case studies. For the poorest performing catchments, this error was in excess of the levels observed in the second publication. Despite this, with a maximum error of approximately ±30%, the models are not rendered intractable. Notably, despite contrasting flow regimes, the hydroecological models developed for the rivers Nar and Thrushel stood out as the best performing models; both were able to achieve good predictive ability whilst exhibiting low parameter uncertainty.

In demonstrating the application of the framework across five hydrologically diverse catchments, it has been shown that delays in hydroecological response may occur in any flow regime type. Indeed, almost half of the indicators were time-offset, with only the River Ribble case study featuring none. Possible reasons for this include limited data availability, seven years of data is reduced to six following the time-offset; and/or structural uncertainty, as illustrated through the negative correlation and highly variable modelling.

To close, the model structure and performance for the principal case study are considered relative to the publication 2, scenario B, model. In the publication, a simplified subset of time-offset indicators was considered, whilst the validation here introduces the full range of variability (capturing the five facets of the flow regime). In the publication, the most important indicators capture flows in hydrological winter, with summer low flows also indicated. These characteristics are clearly reflected in the new model (*Appendix A* – Table A-5). The new model sees the addition of an important rate of change indicator in summer. With the potential to exert a large negative impact on river health, this indicator may be analogous to the median summer flow indicator in the scenario B model. Comparison with publication 2, Figure 7, with Figure 3-5, shows that the more complete model achieves a greater level of consistency: observed and simulated LIFE scores more closely follow the 1:1 line; relative error has fallen, though a small negative bias is introduced; the median error, CDF = 0.5, has fallen from 5% to 2.5%. These findings certainly appear to favour the refined methodology.

8. CONCLUDING REMARKS

Through research question 1, *Can hydroecological models account for a potential delay in hydroecological response?*, this chapter looks to improve current understanding and representation of the hydroecological relationship. To date, delays in hydroecological response have been observed but little studied; the rationale driving further investigation was twofold:

(1) Current modelling efforts may be overlooking potentially critical information (epistemic uncertainty);
(2) The frequency of extreme events is projected to increase under climate change, consequently, recovery time for the instream macroinvertebrate community may reduce. Increasing climate variability represents another factor.

To address this, the first objective (1.1) looked to incorporate the lag through time-offset hydroecological indicators as a proof of concept; this was achieved through publication 1 in River Research and Applications. With this increased complexity, objective 1.2 looked to determine a statistically robust methodology. This was the focus of publication 2, where stepwise selection was compared to an information theory approach.

The above findings were synthesised to establish an updated hydroecological modelling framework (Figure 3-3), the validation and demonstration of which is the focus of *7. Validation.* Here, the framework was applied to five hydrologically diverse case studies.

By not acknowledging the important role of the aquifer in a groundwater-fed catchment, it was shown in publication 2 (scenario B, stepwise selection model) that hydroecological model structures do not always reflect our understanding of catchment hydrological processes. The results *(section 7.2),* suggest that the processes underlying each of the five hydroecological models are sound. With this, the derived hydroecological modelling framework offers a clear answer to research question 1 – it is possible to account for delays in hydroecological response. Indeed, it may be seen as essential – almost half of the ER HIs included in the models were time-offset to account for this lag.

In addressing this source of epistemic uncertainty, whilst improving the statistical robustness and representation of uncertainty, this refined approach is able to occupy the role of stage 1 in the wider coupled modelling framework (Figure 1-4) The inclusion of a statistical measure of importance also satisfies the requirements for the development of the hydrological modelling approach in the next chapter.

Presently, hydroecological modelling (in general) is limited by a lack of data availability and a mismatch in the co-location of ecological and hydrological monitoring sites.

Consideration of time-offset hydrological indicators would reduce this further (shorter time series). This was highlighted through two of the five case studies where model error was high, relative to the other case studies. It was also not possible to account for parameter uncertainty. Data availability is therefore an important consideration when considering the wider applicability of the methodology. Putative solutions and pathways for further research are explored as part of *Chapter 6. Discussion.*

CHAPTER 4. HYDROLOGICAL MODELLING

In this thesis, each research question maps to a stage within the wider proposed framework. In answer to the first research question, the preceding chapter, and two publications, focussed on updating current hydroecological modelling practice (stage 1; Figure 1-4). At this point, the approach now accounts for the phenomena of lag in hydroecological response and can be considered more statistically robust. Notably, the updated approach allows for a measure of statistical importance to be assigned to the ecologically relevant hydrological indicators, identified through the modelling. With this established, the second stage (Figure 1-4) focusses on the replication of the identified ecologically relevant hydrological indicators (ER HIs). Typically, this is achieved through the use of hydrological models (Knight *et al.*, 2011; Murphy *et al.*, 2012); these models represent an abstraction of the hydrologic system at the catchment scale, with precipitation and streamflow serving as the primary input and output respectively. The ER HIs are thus determined from the simulated flow time series. The approach has been subject to criticism, with the ability of hydrological models to capture multiple hydrological signatures in question. Indeed, Murphy *et al.* (2012) argue that

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"the application of general hydrologic models to ecological flow studies is problematic".

This leads to the focus of this chapter and the second research question:

2) Can hydrological modelling be optimised towards the preservation of ecologically relevant characteristics of the flow regime?

2.1. To identify the key challenges inherent to the preservation of these characteristics.

2.2. To determine a robust hydrological modelling approach in support of the preservation of the characteristics identified in objective 2.1.

2.3. To validate and demonstrate the application of the derived methodology (objective 2.2) across a range of hydrologically diverse case studies.

This chapter centres upon a 2019 publication in *Hydrology and Earth System Sciences: Replication of ecologically relevant hydrological indicators following a modified covariance approach to hydrological model parameterization* (Visser-Quinn *et al.*, 2019b). This foreword sets the scene for the publication which follows. First, the motivation for the work is outlined, including a synthesis of the key challenges to the preservation of ER HIs in hydrological modelling (objective 2.1). The alternative hydrological modelling approach which has been developed (objective 2.2) is then introduced. The publication follows, providing further detail, as well as describing the general applicability of the approach through application to the five case studies (see also *Chapter 3 – 7. Validation)*. The afterword weighs the advantages and disadvantages of the modified covariance approach based on the findings in the publication. The chapter closes with concluding remarks, outlining the critical role of this chapter within the wider coupled modelling framework.

1. FOREWORD

1.1 MOTIVATION

Prior to the development of the modified covariance approach, an initial scoping exercise, using the principal case study, the River Nar, was undertaken where a traditional approach to the parameterisation of hydrological models was followed. (Parameterisation is more commonly referred to as calibration; see *Glossary of terms* on page xi for further details.) Based on Grayson and Blöschl (2001), Xu (2002), Blöschl and Montanari (2010), Westerberg *et al.*, (2011), Beven (2012), Pushpalatha *et al.* (2012), Vis *et al.* (2015) and Pool *et al.* (2017), the conceptual framework underpinning this traditional approach was as follows:

(1) Observed data (e.g. precipitation and evapotranspiration) serve as input to a selected hydrological model structure. Models may be lumped, semi-distributed or distributed in nature;
(2) The model structure is parameterised using an algorithm with one or more performance measures which assess the goodness of fit; also known as the objective

function. The modelling goal is typically replication of the observed hydrograph (Gupta *et al.*, 2014);

(3) The parameterised hydrological model is used to produce a simulated flow time series, from which the ER HIs are derived;

(4) The ability of the hydrological model to replicate the ER HIs is then assessed using a range of performance measures.

Based on comparative studies by Perrin *et al*. (2001, 2003), three hydrological models/structures were considered: TOPMODEL (Beven, 1997; Beven and Freer, 2001), Simhyd (a simplification of the model HYDROLOG; Chiew *et al*. (2002)) and the GR suite of daily lumped models (Coron *et al.*, 2017). Consistent with previous studies (Shrestha *et al.*, 2014, 2016; Vis *et al.*, 2015; Pool *et al.*, 2017), the parameterised models performed poorly, with significant error evident across the ER HIs. Accordingly, a review of the literature, outlined in Table 4-1, highlights a number of key challenges inherent to the preservation of ER HIs. How these challenges are addressed through the covariance and the modified covariance approach is discussed in *1.2 Methodology*. The conceptual differences among the traditional, covariance and modified covariance approach are further highlighted in Figure 4-1.

Table 4-1. Summary of key challenges inherent to preservation of ecologically relevant hydrological indices in hydroecological modelling and how the covariance & modified covariance approach redress these. Definitions relating to the sources of uncertainty are provided in *Chapter 1 – 2. State-of-the-art;* see also *Glossary of terms* on page xi.

	Key challenge
1	The objective function strongly influences the ability of a model to consistently replicate ER HIs (Pool *et al*., 2017). To address this, Murphy *et al*. (2012) suggested targeted calibration focussed on the ER HIs. • *Covariance approach.* Model validation and parameterisation explicitly focusses on an identified indicator. Note, only one indicator may be considered. • *Modified covariance approach.* Modification allows for the consideration of a suite of ER HIs.
2	Some studies have employed a broad-brush approach (for example, Shrestha *et al.* (2014) looked at six water resources indicators and the 32 indicators of hydrologic alteration (The Nature Conservancy, 2019)), which does not focus on

catchment specific ER HIs, but rather, a much wider suite of indicators. Both Murphy *et al.* (2012) and Pool *et al.* (2017) stress the need to identify and rank the ER HIs by their relevance (i.e. importance).

- *Modified covariance approach.* Model parameterisation is directly, and solely, informed by the statistical outcomes of hydroecological modelling. Importance is used to define a limit of acceptability for each index.

3 Murphy *et al.* (2012) highlights that ecological flow studies tend to make *"little effort"* (p. 3) to identify and quantify hydrological model uncertainty. A review of recent literature (Shrestha *et al.*, 2014, 2016; Vis *et al.*, 2015; Pool *et al.*, 2017) indicates this remains the status quo.

- *Covariance approach.* The model is validated prior to parameterisation, thereby minimising the influence of disinformative data and model structure on the evaluation of the model suitability.
- *Modified covariance approach.* See covariance approach above. In addition, to account for equifinality, all parameter sets within the limit of acceptability are considered.

4 Vogel and Sankarasubramanian (2003) state that *"A statistician would not attempt to estimate model parameters (calibration) prior to model hypothesis testing (validation), yet hydrologists routinely calibrate their models prior to validation."*; Hosking and Wallis (1997) and Young (2001) make similar comments.

- *Covariance approach and modified covariance approach.* Using generalised sensitivity analysis, the model structure is validated prior to parameterisation. Further, this eliminates the influence of sources of parameter uncertainty (disinformative data and model structure) as part of the validation process (Peel and Blöschl, 2011; Li and Sankarasubramanian, 2012). It must be emphasised that the validity of the hydrological model is only assessed for the domain of applicability, i.e. the ability to achieve the desired modelling goal.

5 There are concerns amongst the scientific community over the methods of assessment used in the evaluation of model performance. For example, in a hydroecological context specifically, the Nash Sutcliffe Efficiency (NSE) is a measure of the goodness of fit relative to the 1:1 line (the observational mean). The NSE produces low scores when variability is high (Gupta *et al.*, 2009), a factor which may render NSE particularly uninformative in this context; NSE is also biased towards high flows (Pushpalatha *et al.*, 2012). The mean absolute relative error is also frequently used despite exhibiting a known bias for large errors (Kim and Kim, 2016).

- *Covariance approach.* Not applicable; beyond the scope of the work.
- *Modified covariance approach.* In the publication, traditional evaluation metrics are used in conjunction with more statistically robust alternatives. Whilst recommendations are made as part of the discussion, the specification of evaluation metrics is not strictly part of the actual model parameterisation approach.

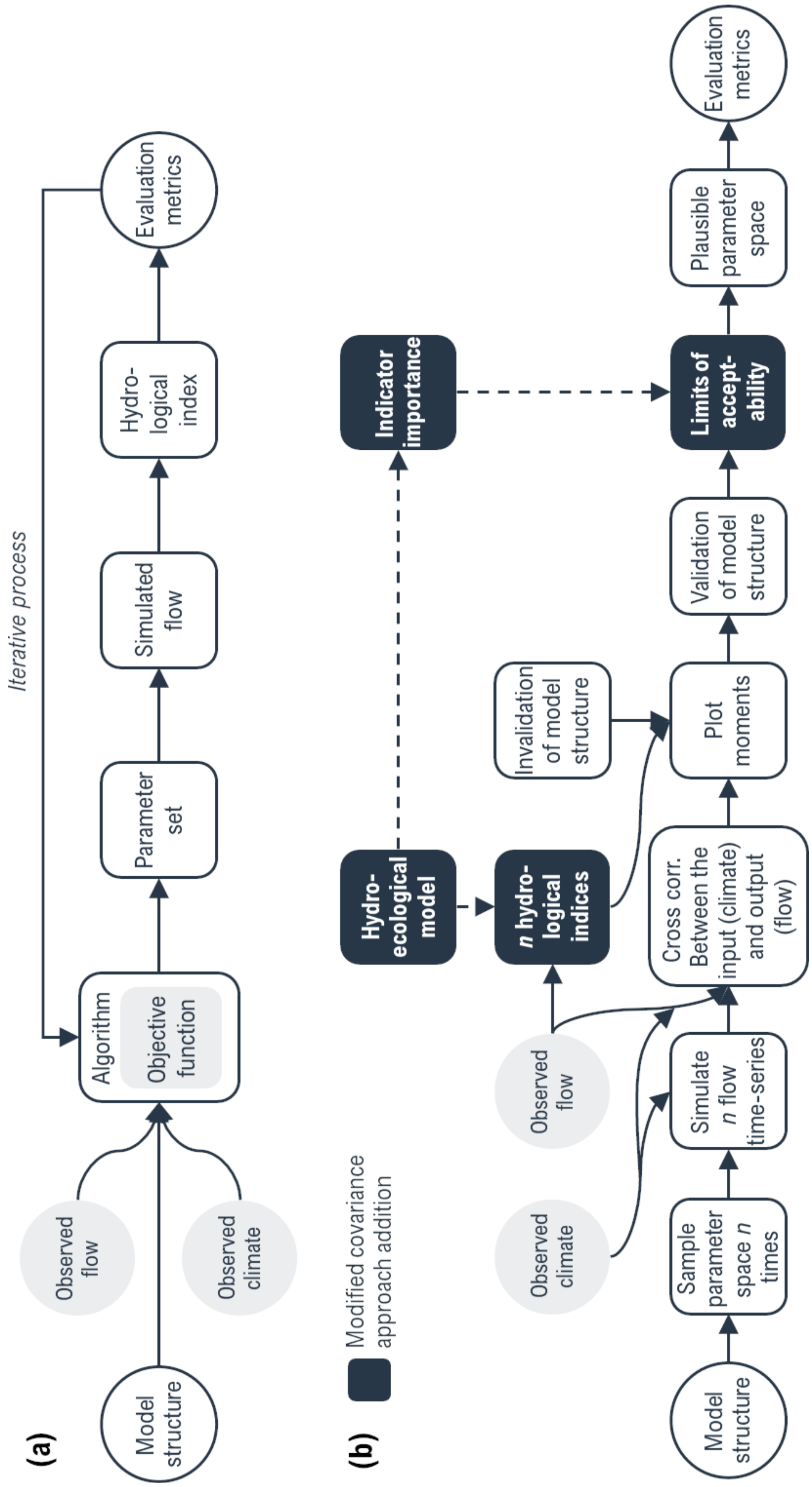

Figure 4-1. Approaches to hydrological model parameterisation. (a) Traditional algorithmic approach. (b) Covariance approach; the dark blue fill indicates additions under the modified covariance approach. *Source: Annie Visser-Quinn.*

1.2 METHODOLOGY

1.2.1 Covariance approach

The method proposed to address these key challenges is a modification of Vogel and Sankarasubramanian's (2003) covariance approach; how the covariance approach addresses these challenges is illustrated in Table 4-1. The methodology of this approach is illustrated in Figure 4-1b previously; a brief description follows.

The covariance approach evaluates the ability of a hydrological model to replicate the observed covariance structure of the model input and output. Using a Monte Carlo (MC) approach, analogous to generalised sensitivity analysis (Spear and Hornberger, 1980), the complete model parameter space is considered. The cross correlation between the input (climate, *c*) and output (streamflow, *Q*), $\rho(c, Q)$, is determined for both the observed data and *n* MC simulations. Similarly, a summary statistic of a hydrological index representing the modelling goal is determined, s_i; in Vogel and Sankarasubramanian (2003) the objective is the replication of the lag one serial correlation. Visualisation of the covariance of climate, streamflow, and the index (how they vary in tandem) reveal the complete sample space that the hydrological model can represent. If the observed covariances lie within the modelled region the model structure is validated and a plausible parameter space identified (from which the model may be parameterised). Where this is not the case, the model is invalidated for the specified modelling goal.

1.2.2 Modified covariance approach

Serving as a proof of concept, Vogel and Sankarasubramanian's (2003) covariance approach was necessarily limited in scope, focussing on the replication of a single indicator. Figure 4-1b (dark blue fill) illustrates the modification necessary to address the key challenges outlined previously (Table 4-1), including the consideration of multiple ER HIs. Instead of considering the covariance of climate, streamflow and a single index, the modified covariance approach assesses each index in turn. Informed by the outcomes of hydroecological modelling in stage 1 of the framework, the measure of importance is used to define limits of acceptability (i.e. a maximum allowable error) for each index.

The publication which follows provides a more detailed introduction to the method, as well as establishing its soundness. The five case studies are introduced in *Chapter 2. Case study catchments,* these catchments were selected to cover a range of hydrological conditions, thereby illustrating the generality of the approach. This is especially important to establish the relative reliability of the model, which, due to the changes in hydrological conditions which may occur under climate change, is extremely pertinent.

As identified in Table 4-1, a key limiting factor of hydrological model parameterisation approaches has been: (1) the lack of focus on catchment specific ER HIs; and (2) not ranking these ER HIs by their relevance. Including this information is central to ensuring the robustness of the coupled modelling framework. Therefore, a comparative assessment of approaches, i.e. the traditional approach versus the modified covariance approach, was considered out with the scope of this thesis.

It is important to note that four, of the five, hydroecological models in publication 3 differ from *Chapter 3 – 7. Validation*. As the principal case study, the River Nar hydroecological model remains constant. The reasons for the differences in models are three-fold:

(1) A time-offset was not included in order to maximise the range of variability captured by the models – for example, in publication 3, the ER HIs capture the frequency facet of the flow regime;
(2) Publishing demands. The hydroecological models for the additional case studies were initially derived as part of revisions to the publication 3 manuscript, they were not subject to further analysis until after publication. The principal aim of this chapter is to optimise hydrological modelling for the replication of ER HIs, therefore these differences have no implication on the validity of the outcomes;
(3) Ecological data availability concerns for two of the five catchments.

2. PUBLICATION 3

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Replication of ecologically relevant hydrological indicators following a modified covariance approach to hydrological model parameterization

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Abstract. Hydrological models can be used to assess the impact of hydrologic alteration on the river ecosystem. However, there are considerable limitations and uncertainties associated with the replication of ecologically relevant hydrological indicators. Vogel and Sankarasubramanian's 2003 (Water Resources Research) covariance approach to model evaluation and parameterization represents a shift away from algorithmic model calibration with traditional performance measures (objective functions). Using the covariance structures of the observed input and simulated output time series, it is possible to assess whether the selected hydrological model is able to capture the relevant underlying processes. From this plausible parameter space, the region of parameter space which best captures (replicates) the characteristics of a hydrological indicator may be identified. In this study, a modified covariance approach is applied to five hydrologically diverse case study catchments with a view to replicating a suite of ecologically relevant hydrological indicators identified through catchment-specific hydroecological models. The identification of the plausible parameter space (here $n \approx 20$) is based on the statistical importance of these indicators. Evaluation is with respect to performance and consistency across each catchment, parameter set, and the 40 ecologically relevant hydrological indicators considered. Timing and rate of change indicators are the best and worst replicated respectively. Relative to previous studies, an overall improvement in consistency is observed. This study represents an important advancement towards the robust application of hydrological models for ecological flow studies.

1 Introduction

Increases in societal water demand and climatic variability raise questions about the long-term sustainability of water resources (Gleick, 1998; Klaar et al., 2014; Davis et al., 2015; Gleick, 2016). As the ecological role of flow is better understood, it has become widely acknowledged as the major determinant of the ecological health of the riverine ecosystem (e.g. Power et al., 1995; Lytle and Poff, 2004; Arthington et al., 2006). Consequently, changes to flow threaten both the ecological health of rivers and their ability to provide the vital ecosystem services upon which humans depend (Vörösmarty et al., 2010; Arthington, 2012).

Beginning in the late 1940s in the United States, the need to balance the conflicting demands of both human society and those of the ecosystem saw the emergence of the environmental flow movement. Environmental flows have been defined under the Brisbane Declaration (2007) as "... the quantity, timing, and quality of water flows required to sustain freshwater and estuarine ecosystems and the human livelihood and well-being that depend on...". Tharme (2003) documented that over 200 formal environmental flow assessment methods had been developed.

Quantifying the relationship between flow and ecology is pivotal for the determination of environmental flows (Bunn and Arthington, 2002; Arthington et al., 2006; Poff et al., 2010; McManamay et al., 2013). Richter et al. (1996) identified five facets of the flow regime required to support the riverine ecosystem: magnitude, frequency, duration, timing and rate of change. Alteration of the flow regime invariably leads to significant ecologic change. To date, over 200 ecologically relevant hydrologic indices (ER HIs) have been pro-

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posed (Olden and Poff, 2003; Monk et al., 2006; Thompson et al., 2013; Mills and Blodgett, 2017). Poff et al. (2010) and Peters et al. (2012) each describe environmental flow frameworks, which call for the determination of ER HIs via hydrological model simulations of flow. At the time of publication (of these frameworks), the application of hydrological models for the determination of ER HIs was in its infancy (Knight et al., 2011). Indeed, early work was largely based on regional statistical approaches which had been in use since the 1960s in the United States (for the determination of water-resource-relevant HIs; for example, see Knight et al., 2011; Carlisle et al., 2010). Murphy et al. (2012) compared such ER HIs against those determined from simulated flows, finding that, without targeted calibration to specific HIs, "the widespread application of general hydrologic models to ecological flow studies is problematic" (p. 667). However, such statistical approaches are unsuitable when assessing the impact of hydrological change on the river ecosystem (e.g. as a result of engineering intervention or under a changed climate) or for the simulation of ecological flows in ungauged catchments. A hydrological modelling approach is thus necessary.

Model performance and consistency are watchwords for this study. Following Euser et al. (2013), model performance is defined as the ability to mimic the behaviour of catchment hydrological processes; consistency represents the ability of the hydrological model to reproduce a suite of ER HIs across parameter sets, hydrological models and catchments.

Significant bias has been observed in hydrological models calibrated following algorithmic model calibration with objective functions and performance measures (Grayson and Blöschl, 2001; Blöschl and Montanari, 2010; Westerberg et al., 2011; Pushpalatha et al., 2012); hereafter this is termed the "traditional approach". For example, when evaluating the suitability of model-simulated HIs (6 water-resource-relevant HIs and 32 ER HIs), Shrestha et al. (2014) observed that water-resource-relevant HIs were well-replicated, whilst notable differences were observed for ER HIs related to the facets of the flow regime duration and rate of change. Informed by recent advances in hydrological modelling more generally (Seibert, 2000; Efstratiadis and Koutsoyiannis, 2010), Vis et al. (2015) compared the ability of single- and multi-criterion objective functions to replicate 12 ER HIs. The best performance was achieved with multi-criterion objective functions, though a consistent negative bias was observed. Despite these advances, overall performance was inconsistent, being dependent upon the ER HI considered. Blöschl and Montanari (2010) observed that the reliability of hydrological modelling approaches which try to "model everything" is analogous to simply "throwing the dice". To address this, they call for a move towards simpler models, tuned to focus on specific characteristics of the flow regime; successful applications of such an approach include Westerberg et al. (2011). Most recently, Pool et al. (2017) considered an array of multi-criterion objective functions using Nash–Sutcliffe efficiency (NSE) and 13 ER HIs. Results were positive, with ER HIs generally well-replicated, though the transposability of the model was subject to greater variability. Those ER HIs not explicitly included in the objective function exhibited the greatest uncertainty overall.

The past 10 years have seen the replication of ER HIs evolve from statistical approaches to single- and multi-objective rainfall–runoff modelling. Whilst improvements have been notable, to date no approach has been able to achieve performance and consistency concurrently, raising questions as to whether these approaches are able to achieve the "right answer for the right reasons". Pool et al. (2017) highlight two points which remain unaddressed: (1) a need to determine which ER HIs are relevant in order to guide model parameterization; and (2) laborious recalibration of the hydrological model is necessary if the suite of HIs is changed. In addition, model evaluation in these studies is singularly focussed on the goodness of fit of the observed–simulated data, while the ability of the hydrological model to capture the relevant hydrological processes is not considered. In this paper we look to redress these limiting factors through the application of a modified covariance approach. The objective of Vogel and Sankarasubramanian's (2003) covariance approach is to identify the plausible parameter space which captures (replicates) the characteristics of a specified HI. This is achieved by focussing on the ability of the hydrological model to capture the observed covariance structure of the input and output time series. The use of covariance relationships in this way is not new, with examples including the modelling of ice sheets (Wu et al., 2010) and ocean salinity (Haines et al., 2006). Vogel and Sankarasubramanian's covariance approach is limited by its focus on a single HI, preventing its use for the determination of a suite of ER HIs. This paper builds on the covariance approach, adapting the methodology to consider a suite of ecologically relevant hydrological indicators; the determination of these ER HIs is based on the outcomes of hydroecological modelling using an information theory approach. To determine the ability of the modified covariance approach in replicating ER HIs, the method is applied to five case study catchments across the UK using the daily models from the GR (Génie Rural) suite of hydrological models (GR4J, GR5J and GR6J, four to six free parameters; Coron et al., 2018).

2 Methods

2.1 Study areas

The UK is home to a wide range of hydrological environments, with 18 different river types (based on catchment area, mean altitude and geology) specified under the Water Framework Directive (Rivers Task Team, 2004). Therefore, to illustrate the generality of the modified covariance approach, it is necessary to apply the proposed methodological approach to a range of catchments with differing characteristics (Andreassian et al., 2006; Gupta et al., 2014). Hydroecological models inform the parameterization of the hydrological models. A mismatch between the co-location of sampling sites as well as the length of time series is a known limiting factor in hydroecological modelling (Monk et al., 2006; Knight et al., 2008). In the UK, this may be addressed, in part, by the recent publication of the UK BIOSYS archive (long-term ecological monitoring data from across England and Wales; Environment Agency, 2018). In this study, ecological and flow time series were paired and catchments assessed in terms of length of the paired dataset (> 10 years), number of sampling sites (> 5), location, catchment area, altitude, catchment steepness ($\mathrm{m\,km^{-1}}$), baseflow index (BFI) and land use. A total of five catchments were selected across the UK, from the north of Scotland to the south-west of England (Fig. A1 in the Appendix); catchment characteristics are summarized in Table 1.

2.2 Hydrological model

The principle of parsimony, known as Occam's razor, posits that a solution should be no more complex than necessary. In the context of hydrological modelling, model simplicity relative to performance is thus made key (Kokkonen and Jakeman, 2002; Perrin et al., 2003; Beven, 2012). To this end, the three lumped models from the GR-J series of daily hydrological models were selected (Perrin et al., 2003): GR4J, GR5J and GR6J (four, five and six free parameters respectively; Perrin et al., 2003; Le Moine, 2008; Pushpalatha et al., 2011). The GR-J series of models have been applied in a variety of hydrological contexts, including climate change impact assessment, water resource forecasting and prediction in ungauged catchments; for examples, see Rojas-Serna et al. (2006), Perrin et al. (2008), Coron et al. (2012, 2017) and Smith et al. (2012).

The three models are based on soil moisture accounting (Fig. A2); precipitation and potential evapotranspiration serve as input. Water is directed to a production store with capacity *x1* mm, split into routed and direct components, and input to unit hydrographs with time base *F(x4)* days. The routed flow is directed to a routing store with capacity *x3* mm. Finally, a groundwater exchange term, *F(x2)*, acts on the routed and direct flow components. The total flow, *Q*, is the sum of the routed and direct flow. To improve general model efficiency (Anderson Michael et al., 2004; Hughes, 2004), GR5J sees the addition of the inter-catchment exchange threshold, *x5*, a function representing the interaction between channel and aquifer flows (Le Moine, 2008). To improve simulations of low flows, the GR6J model includes a parallel store with capacity *x6* mm (Pushpalatha et al., 2011). The models are applied using R package *airGR* (Version 1.0.15.2; Coron et al., 2017, 2018). Parameter limits are summarized in Table A1.

2.3 Determination of ecologically relevant hydrological indicators

The ER HIs were determined based on the outcomes of hydroecological modelling for each catchment. Following Visser et al. (2018), hydroecological models were developed using multiple linear regression with an information theory (IT) approach; see Appendix A2 for details. The IT approach provides a measure of the statistical importance of each ER HI. Consequently, more conclusive statements may be made with regards to the model and the relevance of the ER HIs. To reflect seasonality in the flow regime, the indices are differentiated by hydrological season: winter (ONDJFM) and summer (AMJJAS). Definitions of the ER HIs included in the hydroecological models, and their importance, are available in Table B1. A summary of the distribution of the ER HIs per facet of the flow regime, season and river is provided in Table 2.

2.4 Covariance approach

Continuous (daily) time series of mean flow, precipitation and potential evapotranspiration serve as input to the hydrological models; flow and climate data availability are summarized in Table 1 previously. Potential evapotranspiration was estimated using a temperature-based PE model (Oudin et al., 2005).

The covariance approach was developed by Vogel and Sankarasubramanian (2003), where the aim was to replicate a specific HI rather than the flow time series. The modification of the covariance approach in this study allows for the consideration of a suite of ecologically relevant HIs. The modified covariance approach is implemented over three stages (Fig. 1); stages 1 and 2 are as in Vogel and Sankarasubramanian (2003), with the exception that multiple ER HIs are calculated, with the final stage representing the modification introduced in this study.

– *Stage 1, data preparation*. The parameter space of the three hydrological model structures was sampled within the limits specified in Table A1. With a view to addressing both parameter sensitivity (Tong and Graziani, 2008; Wu et al., 2017) and the number of parameter sets considered, the parameter space was sampled uniformly based on Sobol quasi-random sequences (a quasi-Monte Carlo method). The River Nar catchment served as the "proof-of-concept", consequently, for this catchment; 100 000, 150 000 and 200 000 independent parameter sets were selected for the GR4J, GR5J and GR6J hydrological models respectively; for the remaining four catchments, 10 000 parameter sets were considered (per hydrological model).

  For each parameter set, flow time series were simulated based on the full time series of the observed climate data. For each of these flow time series, a correspond-

Table 1. Summary of case study catchment characteristics. Catchment steepness is unavailable for the Tarland Burn.

		Tarland Burn	River Trent	River Ribble	River Nar	River Thrushel
Flow gauge and catchment	Location	Aboyne	Stoke-on-Trent	Arnford	Marham	Hayne Bridge
	Longitude	−2.7758	−2.1624	−2.2471	0.5472	−4.2424
	Latitude	57.0777	53.0175	53.9962	52.6783	50.6584
	Altitude, gauge (mAOD)	125	113	117	5	67
	Altitude, max (mAOD)	616	331	691	85	273
	Catchment steepness ($m\,km^{-1}$)	–	68	100	23	94
	Bedrock geology	Mafic and felsic igneous	Mud/siltstone, sandstone	Mud/siltstone, sandstone; limestone	Chalk	Mud/siltstone, sandstone
	Baseflow index	0.66	0.44	0.25	0.91	0.39
	Drainage area (km^2)	70.9	53.2	204	153	57.6
	Principal land use	Mountain, heath and bog	Urban and grassland	Grassland	Arable and horticulture	Grassland
Data	Years	2003–2016	1989–2016	2000–2016	1961–2015	1989–2016
	Flow data source	JHI (2018)	NRFA (2018)			
	Climate data source		Met Office (2018a, b)			

Table 2. Number of ER HIs per facet of the flow regime, season (W and S denote summer and winter respectively) and river. Sum totals are detailed in the final columns and rows.

Facet of the flow regime			Tarland Burn		River Ribble		River Trent		River Nar		River Thrushel		Sum per facet
			W	S	W	S	W	S	W	S	W	S	
(M)	Magnitude	Statistic	1	1	1	2	1			1	2		9
		Ratios – log-quantile						2	1			1	4
		Ratios – median-quantile				4	2			3	1	2	12
		Monthly	2				1				1		4
(D)	Duration			2	1		2				1		6
(F)	Frequency		1		1	1	1	1			2		7
(T)	Timing			1		2	2				1		6
(R)	Rate of change					1		1	1	1	1		5
Sum per season per river			4	4	3	10	9	4	2	5	9	3	53

ing set of covariances (between observed climate and simulated flow) and HIs were computed. The observed covariance and HIs are also determined.

– *Stage 2, evaluation*. Under the traditional approach, the hydrological model is evaluated (commonly termed validation) following calibration using an optimization algorithm; this presupposes that the selected hydrological model is able to capture the underlying processes (Oreskes and Belitz, 2001). The covariance approach sees the evaluation of the model structure prior to identification of the plausible parameter space. The model is invalidated, i.e. rejected, when the observed moments lie outwith the simulated moments (sampled parameter space). This may be facilitated through plots of the observed and simulated relationship between the (a) co-

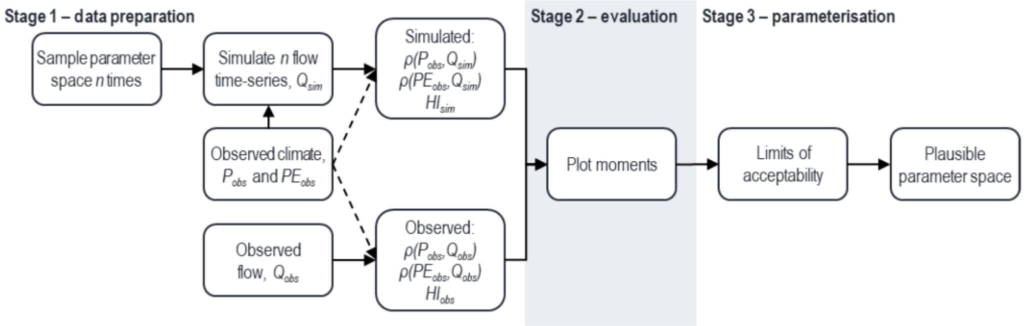

Figure 1. Overview of the three stages of the modified covariance approach to model parameterization.

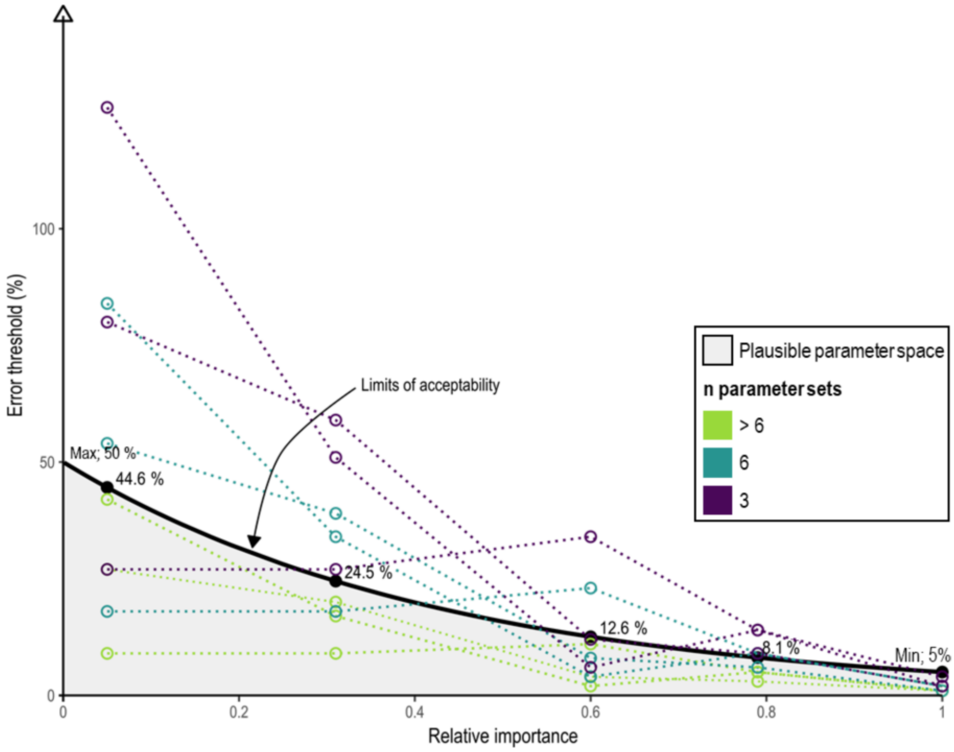

Figure 2. Conceptualization of the limits of acceptability, depicted here as the log-linear relationship between relative importance and the allowable (absolute) error thresholds per indicator and covariance. The limits of acceptability are reduced until $n = 3$ parameter sets lie within the plausible parameter space. In this example, the error threshold ranges from 5 %, where the relative importance is one, to a maximum of 50 %. The maximum allowable error per example indicator is marked.

variance between precipitation and flow, ρ(PQ), and HIs; and (b) covariance between potential evapotranspiration and flow, ρ(PEQ), and HIs. An example for the River Nar is provided in Fig. A3. The moments may also be used to assess model equifinality (the existence of multiple behavioural parameter sets; Beven, 2006; Efstratiadis and Koutsoyiannis, 2010). With a focus on evaluating the hydrological model structure, stage 2 allows consideration of the full length of the hydroclimatological time series; split-sampling may be considered in the parameterization of the model in stage 3.

– *Stage 3, parameterization*. Selection of a model parameter set was based on a specified limit of acceptability (summarized in Fig. 2), i.e. the ability to replicate or minimize the error (percentage difference) between the observed & simulated covariance structures and ER HIs. In Vogel and Sankarasubramanian (2003) the focus was on the replication of a single index, whilst, in this study, the objective was the replication of multiple indices. To this end, a limit of acceptability was specified per index, with each ER HI assigned a maximum error threshold based on their normalized or relative importance. The ER HI importance (Table B1) was normalized (rescaled to a range from zero to one) per catchment and the covariances assigned a relative importance of one, equal to the most important index. The catchment-specific limits of acceptability were specified as the relationship between the relative importance and a user-specified allowable error range. If no parameter sets are selected, the model structure is invalidated and rejected.

Given the large number of ER HIs identified for some catchments, an exponential model of the form $y = e^{mx+c}$ was specified for each catchment, thereby ensuring a focus on the most important indicators (see Fig. 2). In order to account for equifinality, the maximum error was set such that the feasible parameter space was limited to approximately $n = 20$ distinct parameter sets (a discretionary choice made in the absence of any established rule). In Fig. 2, a simplified example is presented where the limits of acceptability are adjusted with a view to identifying a plausible parameter space where $n = 3$.

Note that, dependent on modelling objective, spatio-temporal transposability may be tested in stage 3 following a split-sample approach (Klemeš, 1986). As in Vogel and Sankarasubramanian (2003), the focus here is on methodological development, and thus spatio-temporal transposability is not considered.

2.5 Model performance and consistency

In this study, the ability of the parameterized models in replicating the ecologically relevant hydrological indicators was evaluated through the evaluation metrics detailed in Table 3 (determined with reference to prior studies with similar modelling objectives: Shrestha et al., 2014; Vis et al., 2015; Pool et al., 2017). Metrics were determined across the full time series for each catchment parameter set pairing (e.g. for the River Nar, 54 years of seasonal ER HIs were determined for each of the 23 parameter sets). Three statistical tests were applied, where the goal is the rejection of the null hypothesis ($\alpha = 0.001$). Welch's t-test considers the correlation between the means of the observed and simulated indicators, whilst the KS and CvM (Cramér, 1928; Anderson, 1962) tests look to the distribution of the interquartile range and tails respectively; agreement indicates a relationship between the observed and simulated ER HIs. The hydrologic alteration factor (HAF) is adapted from the IHA approach (Mathews and Richter, 2007). It is a measure of the simulated and observed frequencies of values within three target percentile ranges: 0–25th, 25–75th, and 75–100th. As a measure of distribution, HAF is essentially a simplification of the distribution function. The acceptable range of HAF values is defined as ± 0.33. Finally, two measures of error are determined: model efficiency, or the NSE, and the mean arctangent absolute percentage error (MAAPE), designed to address the limitations inherent to mean absolute relative error (Kim and Kim, 2016).

3 Results

3.1 Model parameters

For all catchments, the low-flow optimized six-parameter GR6J model was invalidated; GR5J was invalidated for all catchments with the exception of the Tarland Burn and River Trent. A summary of the number of parameter sets (per model, per catchment) and interquartile ranges is presented in Table 4, normalized (by the parameter limits specified in Table A1). For further details, see Fig. B1. Being related in function, the parameters of the production (*x1*) and routing (*x3*) store capacities exhibit the greatest range. The groundwater exchange coefficient (*x4*) and inter-catchment exchange threshold (*x5*; where applicable) appear more consistent, whilst the time elapsed for the routing of flow appears inversely related to BFI.

3.2 Model performance and consistency

The ability of the covariance approach in the replication of the ER HIs is considered in terms of performance and consistency. The models are evaluated with reference to the metrics summarized in Table 3 previously. Results are considered by metric, with a focus on the ER HIs with the best and worst performance and consistency.

3.2.1 Statistical tests

A series of tests were applied with a view to determining whether, statistically speaking, the observed and simulated ER HIs come from the same population. The tests focus on the mean (t-test), the central distribution (KS) and tails of the distribution (CVM test). Table B1 in the Appendix details, per ER HI and catchment, the percentage of the parameter sets which did not show a significant level of agreement.

The statistical tests saw perfect agreement across all six timing indicators. With respect to the magnitude indices, the ER HI *BFIr* and the three skewness indicators do not satisfy any of the tests; performance appears irrespective of importance indicated by the hydroecological model or catchment. Magnitude median-quantile ratio agreement was mixed, with high and low flows achieving poor and good agreement respectively. Broadly, frequency indicators indicate a lack of agreement, with only the *PlsFld* index in the River Thrushel exhibiting performance and consistency. The role of statistical importance in the replication of these more complex indicators is also suggested, with *PlsQ75* replicated well in the

Table 3. Descriptions, definitions and optimal values for the applied evaluation metrics. For the statistical tests, the optimal value of $p < 0.001$ represents the significance threshold ($\alpha = 0.001$).

	Metric	Description	Definition (or R function)	Optimal value
Statistical tests	Welch's t-test	Variation on correlation where the two samples have unequal variances. Hypothesis is that two populations have equal means.	stats::t.test(...)	$p < 0.001$
	Kolmogorov–Smirnov test (*KS*)	Tests whether samples come from the same population, i.e. follow the same distribution.	stats::ks.test(...)	$p < 0.001$
	Cramér–von Mises (*CvM*)	Addresses limitations of the KS test: (1) less focused on the central distribution; (2) more equal weighting on the tails of the distribution.	cramer::cramer.test(...) (Franz, 2014)	$p < 0.001$
Distribution	Hydrologic alteration factor (*HAF*)	A factor developed as part of the Indicators of Hydrologic Alteration (Mathews and Richter, 2007). Tests the replicability of sections of the probability distribution (lower-tail, IQR and upper-tail) for a given index.	$\frac{F_{\mathrm{sim}}-F_{\mathrm{obs}}}{F_{\mathrm{obs}}}$ Where F is frequency, the no. of values lying within the probability distribution.	0
Measures of error	Mean arctangent absolute percentage error (MAAPE)	A modification of MARE. Considers the relative error as an angle rather than a slope, reducing the bias of large errors.	$\frac{1}{n}\sum \arctan\left(\frac{I_{\mathrm{obs}}-I_{\mathrm{sim}}}{I_{\mathrm{obs}}}\right)$ Where I is the index value and n the no. observations.	0
	Model efficiency (*NSE*)	Nash–Sutcliffe efficiency. A measure of the goodness of fit of the HI to the 1 : 1 line (observational mean) normalized by the variance.	$1-\frac{\sum(I_{\mathrm{obs}}-I_{\mathrm{sim}})^2}{\sum(I_{\mathrm{obs}}-\overline{I_{\mathrm{obs}}})^2}$ Where I is the index value.	1

Tarland Burn (importance 0.69) and poorly in the River Trent (importance 0.03). More broadly, log-transformed indicators saw better agreement; for example, the more important *MaxMonthlyVar* generally performed poorly, whilst *MaxMonthlyLogVar* saw agreement across all tests and parameter sets.

3.2.2 Distribution – hydrologic alteration factor (HAF)

The hydrologic alteration factor (HAF) is a test of the replicability of the shape of the probability distribution. Figure 3 summarizes the HAF value across the central distribution and tails for each ER HI. There is agreement across the percentile ranges for the majority of the ER HIs considered. Notably, the 19 (of 22; statistics, log ratios and median-quantile ratios) magnitude indicators not pictured achieved an optimal HAF of zero. The 3-monthly indicators (depicted) again highlight relative success in replicating a log-transformed index.

The performance of the six indicators capturing flow pulse events is varied: the central distribution of flood pulses is well-replicated, whilst the upper tail exhibits a consistent large negative bias. The HAF values also serve to highlight some inconsistencies in the performance of the timing indicators. A variable negative bias is in evidence for the index *Mn7MaxJD*; however, in this case, it is worth noting that it is inherently more difficult for a hydrological model to detect and replicate (multiple) short-term events (Pool et al., 2017). Perhaps surprisingly, *Mn90MnJD* is subject to a large positive bias in the lower tail, i.e. the range of the distribution is underestimated. In contrast to *Mn7MaxJD*, this discrepancy may be due to the long(er)-term duration; with seasons of approximately 180 d in length, there are a limited number of values the indicator can take.

3.2.3 Error – MAAPE and NSE

Two measures of error were applied, MAAPE, a modification of the mean absolute relative error (MARE) which reduces the bias of large errors, as well as the more commonplace NSE. The MAAPE for each ER HI is depicted in Fig. 4; to ensure consistency with HAF, acceptable boundaries are specified as ± 0.33 (depicted, horizontal red lines). Overall, the same general patterns may be observed; for ex-

Table 4. Normalized interquartile (IQR) range across the parameter sets for each catchment. The average and mean values across all catchments and models are also indicated. The model GR6J was invalidated; therefore, parameter $x6$ is omitted.

	Tarland Burn		River Ribble	River Trent		River Nar	River Thrushel	Summary	
No. of free parameters	4	5	4	4	5	4	4		
No. of parameter sets	15	4	24	12	4	23	18	Average	Median
$x1$	0.29	0.76	0.48	0.04	0.08	0.31	0.45	0.35	0.31
$x2$	0.13	0.05	0.26	0.11	0.08	0.04	0.07	0.10	0.08
$x3$	0.16	0.25	0.18	0.07	0.51	0.30	0.17	0.24	0.18
$x4$	0.09	0.09	0.03	0.11	0.04	0.01	0.02	0.06	0.04
$x5$	–	0.05	–	–	0.08	–	–	0.06	0.06

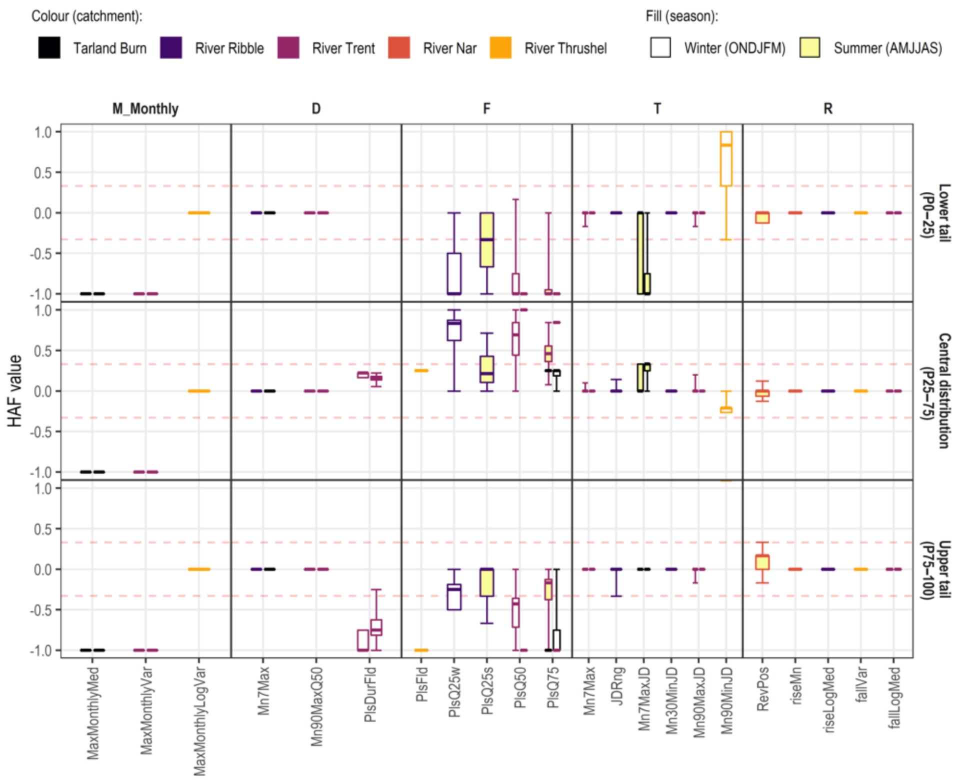

Figure 3. Hydrologic alteration factor (HAF) values for the three percentile ranges for each ER HI; ER HIs are grouped by facet of the flow regime: magnitude (M), duration (D), frequency (F), timing (T) and rate of change (R). The acceptable range of HAF values is defined as ± 0.33 (red dashed line); HAF > 0 represents an increase in frequency relative to that observed, whilst HAF < 0 represents a decrease. All magnitude statistics and ratio ER HIs achieved optimal values (HAF $= 0$) and are not depicted. The four- and five-parameter results are adjacent, left and right respectively, for the Tarland Burn and River Trent.

ample, skew indicators are not well-replicated, log transformation improves the monthly index performance, and timing, with the exception of *Mn90MinJD*, achieves consistently good performance. However, it is clear that the consideration of multiple parameter sets per catchment model leads to variation in the simulated ER HI which may not have been detected by the previous metrics. MAAPE also serves to highlight the difference in performance across the median-quantile ratios, extreme high-flow indices (*Qmax* to *Q05*) are overestimated, whilst the replication of low-flow indices is subject to considerably less (negative) bias.

The NSE is a measure of model efficiency where values less than zero suggest that the observational mean may be a better estimate. In Fig. 5, only ER HIs with NSE > 0 are depicted with the number of parameter sets described as n; for all ER HIs, see Fig. B2.

Seventeen ER HIs achieved NSE values greater than zero; further, the low values of n which are in evidence (Fig. 5) in-

Figure 4. Mean arctangent absolute percentage error (MAAPE) values for each ER HI; ER HIs are grouped by facet of the flow regime: magnitude (M), duration (D), frequency (F), timing (T) and rate of change (R). As per HAF, the acceptable range is defined as ± 0.33 (red dashed line). The four- and five-parameter results are adjacent, left and right respectively, for the Tarland Burn and River Trent.

dicate a lack of consistency across parameter sets. Those ER HIs which have already been shown to perform well are indicated: examples include the low-flow median-quantile ratios, the log-transformed monthly index and the timing indicators more generally.

4 Discussion

There is a clear need to understand the impact of hydrologic change on the river ecosystem. To this end, hydrological models are used to simulate flow time series from which ecologically relevant hydrological indicators are derived. Previous studies (e.g. Vis et al., 2015; Shrestha et al., 2014; Pool et al., 2017) have highlighted the inability of hydrological models to simulate a range, or suite, of ER HIs concurrently. In this study, a modification of the Vogel and Sankarasubramanian (2003) covariance approach was applied to five hydrologically distinct catchments; the focus was on the replication of a suite of ER HIs identified through catchment-specific hydroecological models. The ability of this modified covariance approach, in terms of performance and consistency, was assessed through a series of evaluation metrics.

A range of catchments was, with the main differences lying in the catchment BFI, length of the available time series and the ER HIs. In this study, BFI ranged from 0.25 to 0.91, essentially flashy to groundwater-fed. With the exception of model parameterization, there was no discernible difference in the replication of ER HIs. Similarly, the length of the available time series appears to have made no observable difference to the replicability of the ER HI distributions specifically. In terms of error, MAAPE and NSE, lower overall performance for the shorter time series is expected as a result of sample size sensitivity. Finally, despite consideration of a range of ER HIs with different associated importance, there appears a consistent message in terms of the performance and consistency of similar indices and the facets of the flow regime more broadly.

4.1 Performance and consistency

The consideration of a range of catchments provides a clear picture of the capacities of the hydrological models as well as the relative success of the covariance approach. Overall, replication of the ER HIs was good. Timing and log-transformed indicators (*logQVar*, *MaxMonthlyLogVar* and the log-quantile ratios) were among the most consistent and well-replicated across the range of catchments. The results are broadly consistent with a number of recent studies

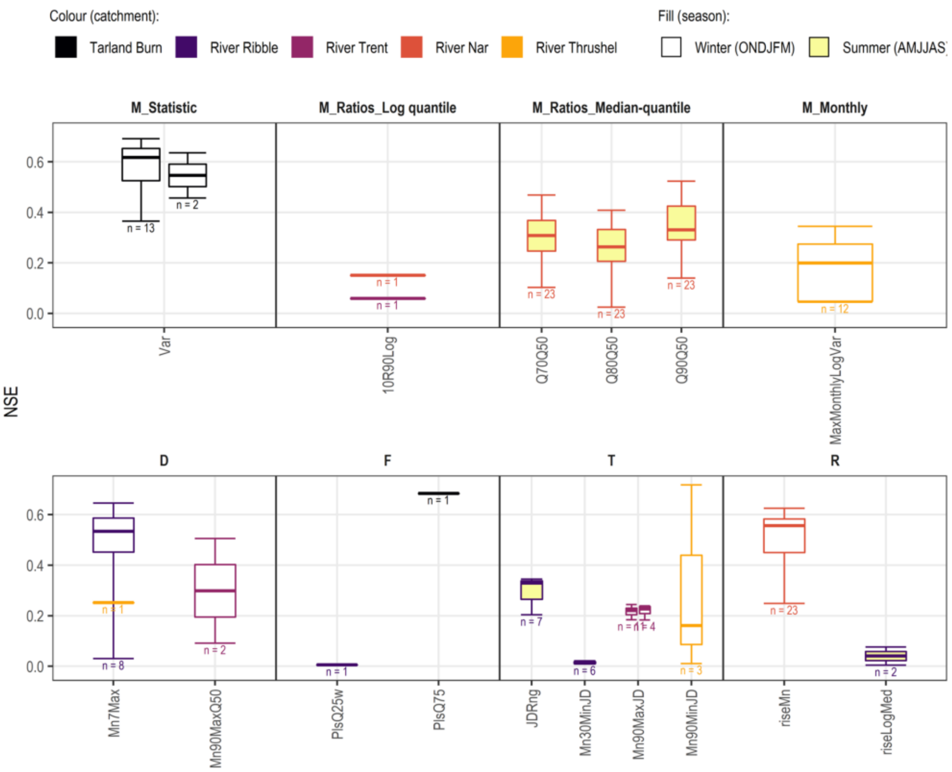

Figure 5. Nash–Sutcliffe efficiency (NSE) for each ER HI where NSE > 0 (model skill greater than the observational mean); see Fig. B2 for all NSEs. The ER HIs are grouped by facet of the flow regime: magnitude (M), duration (D), frequency (F), timing (T) and rate of change (R). The four- and five-parameter results are adjacent, left and right respectively, for the Tarland Burn and River Trent.

(Melsen et al., 2018; Mackay et al., 2019; Worthington et al., 2019) where timing and duration indicators are among the indicators with the highest prediction accuracy. Difficulties were observed in replicating frequency and rate of change indices. Replication of indicators incorporating the seasonal median flow (Q50) was also poor, with large positive biases frequently observed. This may be observed directly through comparison of the replication of Q01 and Q01Q50 in the River Trent where the degree of error can be seen to markedly increase. Recent studies by Mackay et al. (2019) and Worthington et al. (2019) also observed higher error rates for monthly indicators.

4.1.1 Suitability of ER HIs in hydrological modelling

This, and previous studies, have observed difficulties in the replication of frequency ER HIs (flow pulses). This begs the following questions. Is this a product of the covariance approach? An inherent limitation of hydrological models more generally? Or is this related to the nature of the indicator itself? A review of the simulated flow suggests the latter. There is a tendency for the simulations to identify shorter more frequent pulses, whilst the observed pulses are longer and less frequent. For instance, the median error (MAAPE) for *PlsQ50* (the number of pulses above a baseline Q50 threshold) on the River Trent was 0.75; this falls to 0.368 if the focus is on the total duration of the pulses. The pooling of events with an inter-event time below some threshold, as per the inter-event time and volume criterion (Gustard and Demuth, 2009) for example, may serve to improve the replication of the pulse indicators. It should be noted that, in this study, this limitation does not extend to flood pulses (*FldPls*) due to the much larger inter-event time, thus allowing for better replication of flood pulses overall.

In multiple cases, this study observed difficulties in replicating those ER HIs which are considered relative to the median seasonal flow. Comparison of the indicators Q01 and Q01Q50 in the same catchment indicates that the lack of direct consideration of median flows in the parameterization of the model may be a limiting factor. Indeed, it may be that the decomposition of such indicators into their component parts, e.g. Q01 and Q50, may lead to better replicability overall. Similarly, the results indicate that log transformation of flows may lead to improvements in the replicability of certain ER HIs.

Further work is required to confirm this premise.

4.1.2 Suitability of evaluation metrics

There is a lack of consistency in the evaluation metrics considered in the evaluation of hydrological model performance. Further, these studies make use of metrics which exhibit known bias, for example, mean absolute relative error (MARE; Kim and Kim, 2016; and NSE, Gupta et al., 2009; Pushpalatha et al., 2012; Vis et al., 2015). For the measure of error, this study replaced the former with MAAPE (see Table 3). The reasons for the consideration of NSE in this study were twofold: (1) application of NSE is the norm; and (2) to illustrate the limitations of this measure. The limitations of NSE are frequently cited as low scores where there is high variability (Gupta et al., 2009) as well as a bias towards high flows (Pushpalatha et al., 2012). Additionally, the NSE is scaled by the standard deviation, rendering it incomparable across catchments (Gupta et al., 2009). In this study, only 17 of the ER HIs achieved NSE > 1; i.e. the simulations are better than an estimation based on the observed mean. Similar observations were made in Vis et al. (2015). It can be concluded that, given this lack of robustness, NSE is not a suitable evaluation metric in studies such as this one.

4.2 Advantages and limitations of the modified covariance approach

In this section we consider the general advantages of the modified covariance approach, relative to the traditional approach; this is followed by consideration of the hydroecological modelling requirements. It is clear that no approach has been able to achieve adequate performance and consistency in the replication of more complex ER HIs, specifically those related to rate of change. Shrestha et al. (2014) observed difficulties in replicating low flows, the duration of flow pulses, and monthly flows specifically. In this study, no such observations have been made with regards to low flows and duration; indeed, these may be considered to be relatively well-replicated across all catchments. Poor replication of monthly ER HIs does however persist; log-transformed variations of these indicators may represent a viable alternative. Whilst Pool et al. (2017) saw improvements (relative to Shrestha et al., 2014; Vis et al., 2015), the need to calibrate the model to each ER HI in question would strongly call into question the reliability of the hydrological model (due to the inability of the hydrological model to simulate catchment hydrological processes simultaneously). The consistency with which (the majority of the) ER HIs are replicated here illustrates that this is not a necessary limitation of hydrological models. A lack of consistency in ER HIs demonstrating elevated levels of variability, such as high flows, is to be expected due to the dynamic nature of inter-annual weather patterns (Pool et al., 2017).

4.2.1 General advantages

Here follows a brief discussion of the general advantages of the modified covariance approach. First, uncertainty is reduced via a number of avenues.

- *Disinformative data*. Models calibrated following a traditional approach are particularly sensitive to measurement error (Westerberg et al., 2011). Lack of agreement in the observed–simulated time series, even for a single event, may bias the objective function, leading to rejection of an otherwise well-performing parameter set (Beven, 2010; Westerberg et al., 2011). Methods which do not focus on the replication of time series directly, such as the modified covariance approach, are known to limit the influence of input uncertainty (Westerberg et al., 2011; Euser et al., 2013).
- *Validation of model structure*. Consideration of the observed and simulated moments allows the user to evaluate the ability of the hydrological model structure in capturing the hydrological processes in the catchment, thus ensuring the selection of the optimal model (structure).
- *Equifinality*. Equifinality, reaching the same outcome by different means, is a major challenge of hydrological modelling. In the modified covariance approach the entire parameter space is considered at the outset. A plausible parameter space is determined by focussing on the region which is best able to replicate the characteristics of the HIs, thereby reducing the epistemic uncertainty associated with accounting for equifinality (Wu et al., 2017).

Finally, whilst the large number of simulations required under the modified covariance approach may seem prohibitive, this demand may be offset. Unlike the traditional approach, where selection algorithms may introduce issues of speed and accuracy (Seibert, 2000), finite time is needed to apply the covariance approach. All simulations of the hydrological model are performed at the outset; once the full suite of parameter sets have been simulated, the hydrological model need not be run again. Under a more traditional approach, such as in Pool et al. (2017) where the ER HIs serve as the objective, the HIs must be specified at the outset. This is not the case in the modified covariance approach, where the n Monte Carlo simulations can be performed in advance of HI selection. Thus, multiple suites of ER HIs may be considered (e.g. all rate of change or magnitude indicators) with limited additional time outlay.

4.2.2 Hydroecological model requirements

The explicit consideration of the outcomes of hydroecological modelling is perhaps both the most significant advantage and disadvantage of the modified covariance approach.

Whilst hydrological modelling informed by the outcomes of hydroecological studies is not new, for instance, Pool et al. (2017) was informed by Knight et al. (2014), the novelty of this approach lies in the explicit consideration of the statistical importance of the ER HIs, identified through hydroecological modelling. The consideration of the relative importance of each ER HI allows a large suite of ER HIs (7 to 13) to be considered with no apparent penalties. Further, contrary to expectations, a large number of important ER HIs (> 0.5) has no impact on replicability. In the case of the River Ribble, where a total of 13 ER HIs were considered, 7 had an importance greater than 0.5. Similarly, through this approach, a high weighting is not needlessly attributed to ER HIs with low importance.

The need for a hydroecological model represents the major limiting factor due to the requirement for long-term hydroecological time series. Historically, hydrological and ecological data were collected for different objectives (Poff and Allan, 1995; Knight et al., 2008; Monk et al., 2008), leading to a mismatch in temporal and spatial coverage. High levels of disparity in sampling and gauging sites inevitably introduce noise into the model. However, the availability of national ecological datasets, such as BIOSYS in the UK, may serve to offset the issue of data availability. Such datasets may be used to develop regional hydroecological models based on flow regime type and the assumption of homogeneity in environmental conditions. The modified covariance approach may also be applied without a numerical measure of the relative importance of each indicator; this would however introduce an element of subjectivity into the parameterization of the model.

4.3 Wider applicability and further work

The modified covariance approach is able to provide statistically robust simulations and projections of ER HIs for applications such as environmental flow assessment or in assessing the hydroecological impact of climate change such as in Visser et al. (2019a, b). However, the applicability of the approach may not be limited to hydroecological studies and the simulation of ER HIs (e.g. replication of hydrological signatures). In this context, example applications could include the replication of water resource management indicators (monthly, seasonal and annual flows). Such applications would require consideration of a statistical model for the determination of the statistical importance of indicators. The approach may also be used in the development of regional hydrological models, thereby facilitating the simulation of ER HIs in ungauged catchments. Finally, the clarity with which model structures are accepted or rejected makes the approach apt for use in combination with model selection frameworks such as the Framework for Assessing the Realism of Model Structures (FARM; Euser et al., 2013).

5 Concluding remarks

This study considered the performance and consistency of a modified covariance approach in the replication of ecologically relevant hydrological indicators. Application across five hydrologically diverse catchments showed a consistent level of performance across the majority of ER HIs; the timing facets of the flow regime were best replicated, whilst rate of change indicators saw the poorest performance and consistency. Relative to similar studies, there was an overall improvement in consistency; thus, this study represents an important advancement towards the robust application of hydrological models for ecological flow studies. The explicit consideration of hydroecological modelling outcomes allows the hydrological model to be tuned to parameters based on statistical importance. A further major advantage of the modified covariance approach lies in the identification of the plausible parameter space which best captures (replicates) the characteristics of the ER HIs, thereby providing a greater understanding of the suitability, limitations and uncertainties of the hydrological model structure.

Data availability. The hydroclimatological data used for all catchments (except the Tarland Burn) are freely available from the NRFA (2018), Met Office (2018a, b). Data for the Tarland Burn were provided to Heriot-Watt on request for this study by the James Hutton Institute (JHI, 2018).

Appendix A: Method

A1 Case studies

Table A1. Parameter limits for the hydrological models.

	Description	Limits
$x1$	Capacity of production store (mm)	(100, 1200}
$x2$	Groundwater transfer (mm d^{-1}; positive indicates flow *from* aquifer)	(−5, 25}
$x3$	Capacity of routing store (mm)	(20, 1000}
$x4$	Time lag between rainfall event and flow (days)	(0.5, 30}
$x5$	Inter-catchment exchange threshold (–)	(−5, 25}
$x6$	Capacity of parallel routing store (mm)	(20, 1000}

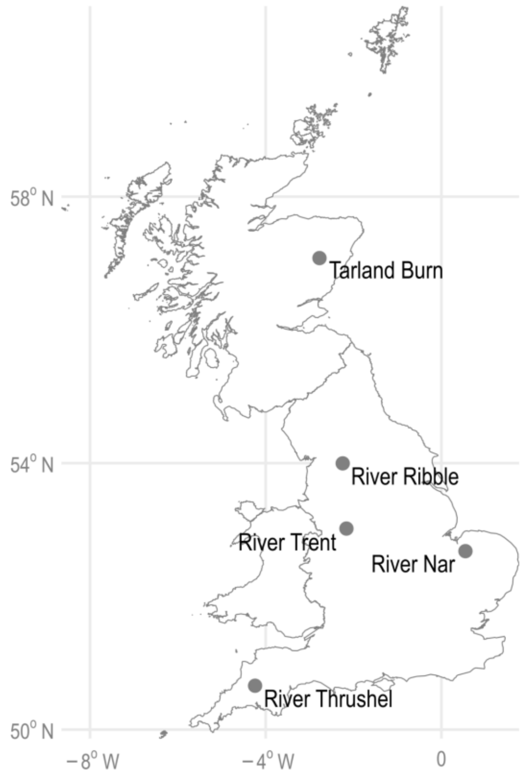

Figure A1. Distribution of the case study catchments across the UK.

A2 Hydroecological modelling

Based on Olden and Poff (2003) and Monk et al. (2006), daily mean flow data were used to derive 63 hydrological indices per hydrological season: winter (ONDJFM) and summer (AMJJAS); for the data source, see Table 1. Principal component analysis (PCA) was applied to identify those indices which describe the major aspects of the flow regime whilst minimizing redundancy.

Macroinvertebrates serve as the proxy for ecological response. Response is determined using the Lotic-invertebrate Index for Flow Evaluation (LIFE), accounting for macroinvertebrate flow velocity preferences (Extence et al., 1999). For four out of five case studies LIFE scores were determined to family level; data for the River Nar, obtained directly from the Environment Agency, were available to species level. The modelling focused on spring ecological activity (the period of peak activity and largest consistent availability of data).

Following Visser et al. (2019b), an information theory approach to modelling was taken in order to provide a quantitative measure of support for parameters and candidate models. Inference is made from multiple models through model averaging. In summary: (1) the candidate models are evaluated with respect to the second-order bias-corrected Akaike information criterion (AIC) (following Burnham and Anderson, 2002; see also Visser et al., 2019b); (2) a best approximating model is inferred from a weighted combination of all the candidate models; (3) the parameters are ranked, such that the highest value represents the most important in the model; (4) filters are applied to remove parameters where the estimate and confidence intervals are zero (i.e. certainty that the index is not to be included) and to reduce the model to the parameters which describe 95 % of the cumulative information. For further details, see Visser et al. (2018, 2019b).

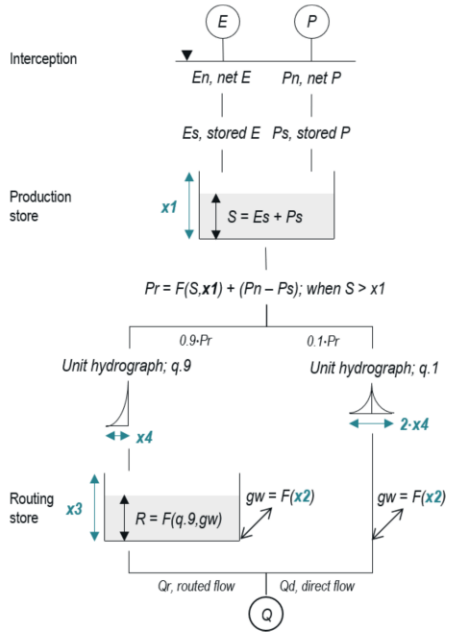

Figure A2. Structure of the GR4J hydrological model, based on Perrin et al. (2003). The five-parameter GR5J sees the addition of $x5$, inter-catchment exchange parameter, at the same locations as $x2$, whilst GR6J sees the addition of a store parallel, capacity $x6$, to the routing store.

A3 Hydrological modelling

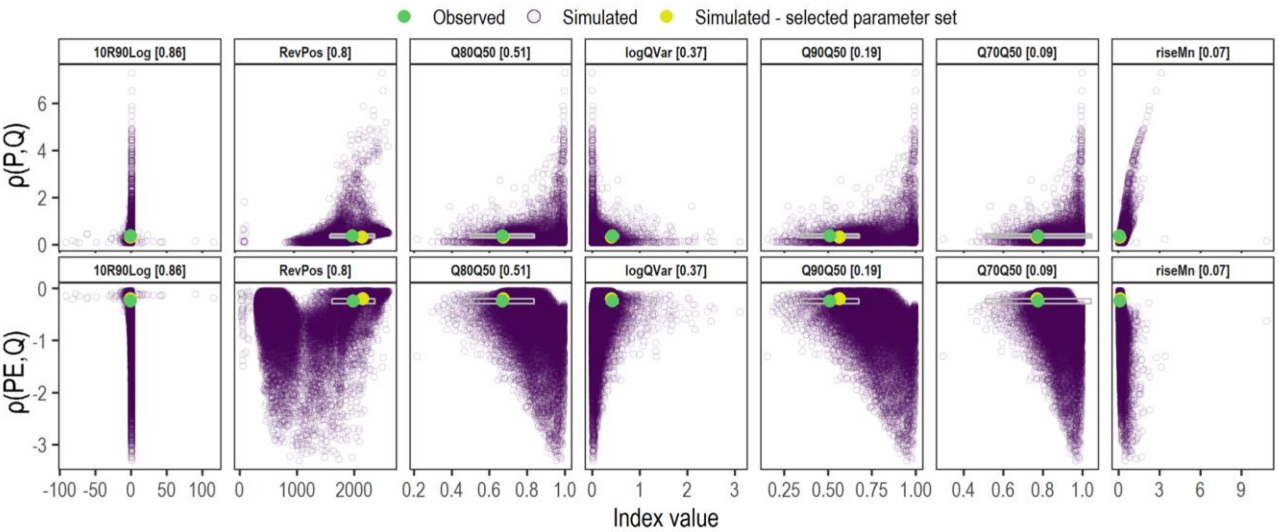

Figure A3. Observed and simulated moments for the 100 000 Monte Carlo simulations using the GR4J model for the River Nar case study. The grey boxes depict the boundaries of the limits of acceptability per index. One of the selected parameter sets, $i = 73\,952$, is highlighted (yellow).

Appendix B: Supplementary results

B1 Ecologically relevant hydrological indices and test statistics

Table B1. Ecologically relevant hydrological index descriptions; grouping is by facet of the flow regime. Seasons are indicated in regular font (winter) and in bold font (summer). Subsequent columns are catchment-specific, denoting ER HI importance, with the results of the statistical tests detailed in Table 3. In the table, a flood threshold is the flow equivalent for a flood recurrence interval of 1.67 years (on the baseline).

			Tarland Burn*					River Ribble					River Trent*					River Nar					River Thrushel				
Index	Description	Units	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails
Magnitude – statistic																											
IQR	Interquartile range of flow.	$m^3 s^{-1}$	**0.43**	**0**	**0**	**0**	**0**																				
Var	Variance in flow.	–	0.46	0	0	0	0																				
Q01	Q1 flow (extreme high flow).	$m^3 s^{-1}$						0.32	0	83.3	70.8	87.5															
Sk	Skewness, mean relative to median.	–						**0.11**	**0**	**100**	**100**	**100**											0.88	0	100	100	100
SkRel	Relative skewness, mean minus median, relative to median.	–						**0.09**	**0**	**100**	**100**	**100**															
Sk100	Range relative to the median.	–																					0.38	0	100	100	100
logQVar	Variance in log-transformed flow.	–																**0.37**	**0**	**0**	**0**	**0**					
BFIr	The seasonal BFI relative to baseline BFI.	–											0.03	0	100	100	100										

Table B1. Continued.

Index	Description	Units	Tarland Burn*					River Ribble					River Trent*					River Nar					River Thrushel				
			Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails
Magnitude – ratios – log-quantile																											
10R90 Log	Log-transformed ratio, *xx*th to *yy*th percentile flow.	–											**0.97**	**100**	**0**	**8.3 — 100**	**0**	0.86	100	0	0	0					
20R80 Log																							**0.94**	**100**	**0**	**0**	**0**
25R75 Log													**0.97**	**100**	**0**	**8.3 — 100**	**0**										
Magnitude – ratios – median-quantile																											
MaxQ50	Max. flow relative to median (extreme high flow).	–																					0.32	0	100	100	100
Q01Q50	Q*xx* flow relative to median (high flow).	–						**0.53**	**0**	**100**	**100**	**100**	0.03	0	100	100	100										
Q05Q50								**0.4**	**0**	**100**	**100**	**100**															
Q20Q50													0.03	0	16.7 — 100	66.7 — 100	58.3 — 100										
Q60Q50	Q*xx* flow relative to median (low flow).	–																					**0.97**	**0**	**72.2**	**33.3**	**72.2**
Q70Q50								**0.88**	**0**	**83.3**	**66.7**	**83.3**						**0.09**	**0**	**0**	**0**	**0**	**0.99**	**0**	**77.8**	**55.6**	**72.2**
Q80Q50								**0.38**	**0**	**83.3**	**75**	**87.5**						**0.51**	**0**	**0**	**0**	**0**					
Q90Q50																		**0.19**	**0**	**0**	**0**	**0**					

Table B1. Continued.

			Tarland Burn*					River Ribble					River Trent*					River Nar					River Thrushel				
Index	Description	Units	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails
Magnitude – monthly																											
Max Monthly Med	Median of max. monthly flow.	$m^3\,s^{-1}$	0.7	0	0—25	0	0																				
Max Monthly Var	Variability in max. monthly flow.	–	0.45	0	0	0	0						0.92	100	33.3—100	91.7—100	91.7—100										
Max Monthly LogVar	Variability in max. monthly log-transformed flow.	–																					0.45	100	0	0	0
Duration																											
Mn7 Max	Mean of the 7 d cumulative max. flow.	$m^3\,s^{-1}$	**0.53**	**0**	**0**	**0**	**0**	0.14	0	20.8	33.3	25											0.5	0	94.4	77.8	88.9
Mn90 MaxQ50	Mean of the 90 d cumulative max. flow relative to the median.	–	**0.53**	**0**	**0**	**0**	**0**						0.06	0	25—100	16.7—100	33.3—100										
PlsDur Fld	Duration of pulses above a (baseline) flood threshold.	Days											0.02	100	0	0	50—25										
PlsDur Q75Var	Variation in the duration of pulses below a Q75 (baseline) threshold.	–																									

Table B1. Continued.

			Tarland Burn*					River Ribble					River Trent*					River Nar					River Thrushel				
Index	Description	Units	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails
Frequency																											
PlsFld	No. of pulses above a (baseline) flood threshold.	Count																					0.41	100	0	0	55.6
PlsQ25w	No. of pulses above a Q*xx* (baseline) threshold.	Count						0.64	0	91.7	83.3	95.8															
PlsQ25s								**0.58**	**0**	**66.7**	**70.8**	**83.3**															
PlsQ50													0.04	0	100	100	100										
PlsQ75	No. of pulses below a Q*xx* (baseline) threshold.	Count	0.69	0	0	0	0						**0.03**	**0**	**100**	**100**	**100**										
Timing																											
JDRng	Range in the Julian days for the max. and min. daily mean flow.	JD						**0.73**	**0**	**0**	**0**	**0**															
Mn7 MaxJD	Julian day of the mean 7 d max. flow.	JD	**0.78**	**0**	**0**	**0**	**0**						0.94	0	0	0	0										
Mn30 MinJD	Julian day of the mean 30 d min. flow.	JD						**0.67**	**0**	**0**	**0**	**0**															
Mn90 MaxJD	Julian day of the mean 90 d max. flow.	JD											0.03	100	0	0	0										
Mn90 MinJD	Julian day of the mean 90 d min. flow.	JD																					0.88	100	0	0	0

Table B1. Continued.

			Tarland Burn*					River Ribble					River Trent*					River Nar					River Thrushel				
Index	Description	Units	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails	Importance	Normal	Mean	IQR	Tails
Rate of change																											
RevPos	No. of days when flow increases (positive reversals).	Days																**0.8**	**0**	**100**	**100**	**100**					
riseMn	Mean rise rate (flow increasing).	$m^3\ s^{-1}$																0.07	0	0	0	0					
riseLog Med	Median log-transformed rise rate (flow increasing).	$m^3\ s^{-1}$						**0.55**	**0**	**0**	**0**	**4.17**															
fallVar	Variation in fall rate (flow decreasing).	–																					0.16	0	100	100	100
fallLog Med	Median log-transformed fall rate (flow decreasing).	$m^3\ s^{-1}$											**0.93**	**100**	**91.7 — 75**	**100**											

* Four- and five-parameter models were applied to both the Tarland Burn and River Trent. Single-digit entries should be interpreted as being the same across both models; where entries are separated, e.g. for *10R90Log*, the former represents GR4J and the latter GR5J.

B2 Model parameters

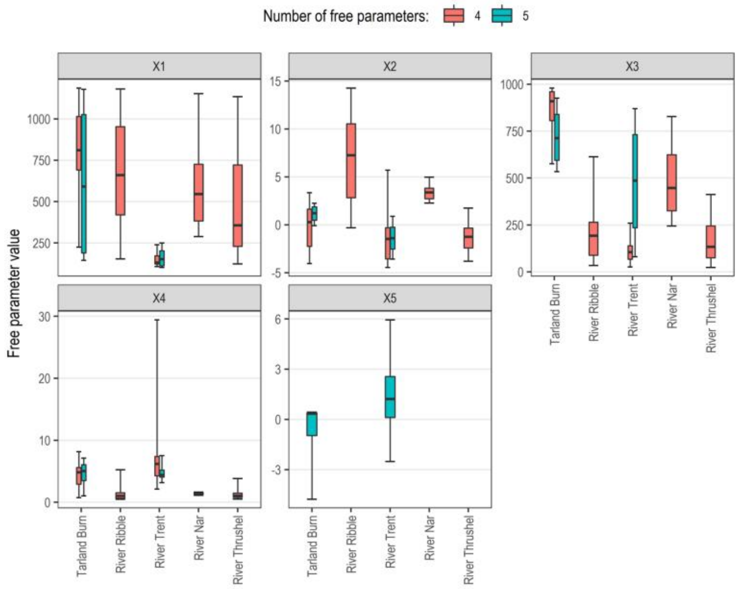

Figure B1. Boxplots of the parameter values across the 100 selected models. The whiskers represent the maximum and minimum values observed.

B3 Nash–Sutcliffe efficiency

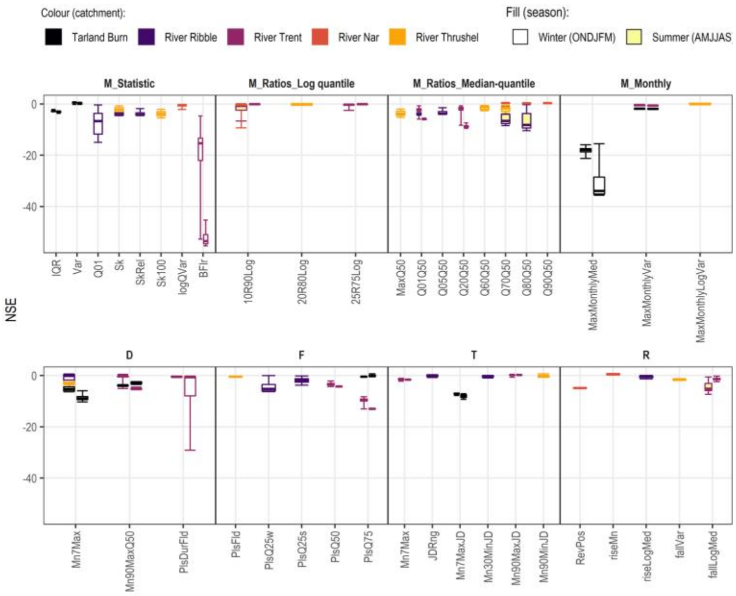

Figure B2. NSE for each ER HI; see Fig. 5 for NSE > 0. The four- and five-parameter results are adjacent, left and right respectively, for the Tarland Burn and River Trent.

Author contributions. AV developed the methodology and code and performed the data analysis. AV prepared the manuscript, whilst LB provided review and edits. Both LB and SP provided supervision.

Competing interests. The authors declare that they have no conflict of interest.

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3. AFTERWORD

In terms of the best and worst replicated indicators, timing and rate of change respectively, the results across the five case study catchments are shown to be broadly consistent with previous work (Shrestha *et al.*, 2014, 2016; Vis *et al.*, 2015; Pool *et al.*, 2017). Whilst overall there was a noticeable improvement in performance and consistency, the inability to adequately replicate more complex indicators, such as rate of change, suggests that hydrological models may be missing some key understanding of catchment hydrological processes.

The covariance approach introduces a way to assess the suitability of a hydrological model for a given modelling goal. This was illustrated in the publication with the invalidation of the six-parameter model, GR6J, across all catchments. The exclusion of this, the most complex option, may be an indication of the discriminatory power of the methodology; any more definitive statement is made impossible due to the consideration of only five catchments.

Whilst the modified covariance approach makes significant steps towards addressing the identified key challenges, a number of areas do require improvement, and additional limitations are also introduced as a result of the method. One of the principal advantages of the approach, the weighting of indicators by importance, may also represent the biggest limitation. The hydroecological data requirements may be hindered by the spatio-temporal mismatch between hydrological and ecological data which often occurs (Monk *et al.*, 2006). In such cases, it is either not possible to derive the required model, or the model may be subject to greater levels of uncertainty. However, it is worth highlighting that, a traditional approach incorporating weighted indices would be subject to the same limiting factor.

The application of the modified covariance approach focussed on a number of lumped models which provide a simplistic representation of the catchment as a homogeneous whole. A comparative study across a range of catchments and model types (including semi-distributed and distributed, where flow is determined at the sub-catchment and grid level respectively) would reveal whether similar improvements in performance and consistency may be observed. However, the increased number of parameters associated with these models may introduce a further challenges (Vogel and Sankarasubramanian, 2003), the identification of appropriate sampling strategies so as to manage the computational requirements.

The purpose of validation under the traditional approach concentrates on the spatial and/or temporal transposability of the model (Klemeš, 1986). The assessment of temporal transposability is useful where the hydrological model is to be used for climate change impact assessment: the model must be able to make suitably accurate predictions outside the period it was calibrated. The publication focusses on the introduction of the method and the underlying science, thus, temporal validation, through, for example, split sampling, was considered out with the scope of the work: *"As in Vogel and Sankarasubramanian (2003), the focus here is on methodological development, and thus temporal transposability is not considered."* (Visser-Quinn *et al.*, 2019b, p. 3284).

Where split sampling is undertaken, the time series may be split in two; the moments from each are used to identify the plausible parameter space. If there is no agreement between the parameter spaces, the model is invalidated.

4. CONCLUDING REMARKS

This chapter looks to establish whether hydrological modelling can be optimised towards the preservation of ecologically relevant characteristics of the flow regime. This was explored through two objectives. To achieve objective 2.1, five key challenges were identified: (1) the use of objective functions; (2) the lack of catchment specific ER HIs; (3) the need to minimise and characterise uncertainty; (4) the lack of validation; and (5) the use of unsuitable evaluation metrics. With a specific focus on robustness, objective 2.2 looked to the development of a hydrological modelling with these key challenges in mind. Vogel and Sankarasubramanian's (2003) covariance approach was identified as capable of addressing a number of these limitations. Based on sound statistical principles, and linking directly to the underlying physics, the approach represents an opportunity to get the right answers, for the right reasons. This further reduces the potential for errors exacerbated under future climates (assuming stationarity).

Stage 1 of the wider framework sees the determination of a hydroecological model. In order to derive hydroecological projections, this model must be coupled with a hydrological model capable of replicating the identified ER HIs. The modified covariance approach introduces limits of acceptability (informed by a hydroecological model), thereby allowing for the consideration of this suite of ER HIs.

By departing from the normal modus operandi in the field, the modified covariance approach goes some way to addressing the identified challenges. Further, application of the approach to five case studies showed improvements in performance and consistency of the replication of ER HIs. It can be concluded that this work represents an important advancement towards the robust application of hydrological models for ecological flow studies and thus provides a clear answer to research question 2.

CHAPTER 5. COUPLED MODELLING FRAMEWORK

Chapter 5 represents the culmination of this body of work. Here, the findings are pulled together to form a coupled modelling framework. The first two stages of the framework look to establish the two component models (Figure 1-4): a hydroecological model and a hydrological model. The development and optimisation of approaches for deriving these component models was the focus of chapters 3 and 4 previously. Guided by the final research question and associated objectives below, this chapter focuses on the completion of the coupled modelling framework.

> **3) Can climate change projections be used in the determination of quantitative hydroecological outcomes?**
>
> 3.1. To characterise and minimise the uncertainty introduced to the coupled modelling framework.
>
> 3.2. To determine a coupled modelling framework to assess the hydroecological impact of climate change.
>
> 3.3. To validate and demonstrate the coupled modelling framework for the principal case study, the River Nar.

The characterisation and minimisation of uncertainty forms the backbone of the coupled modelling framework. Therefore, prior to its completion, a synthesis of the uncertainty is provided in *1. Characterisation and minimisation of uncertainty*. The remainder of the chapter is centred around the final two research objectives (3.2 and 3.3) which are addressed through the 2019 publication in *Environmental Modelling & Software: A coupled modelling framework to assess the hydroecological impact of climate change* (Visser *et al.*, 2019b). A foreword and afterword serve to put the paper in context. The chapter closes with concluding remarks; further commentary on the complete framework follows in *Chapter 6 – Discussion*.

1. CHARACTERISATION AND MINIMISATION OF UNCERTAINTY

Water has been identified as the principal medium through which the impacts of climate change will be felt (Arthington, 2012b; Cisneros *et al.*, 2014). Taken together with the imprecise nature of climate projections, this necessitates the characterisation and minimisation of the uncertainty attached to the projected hydroecological impact of climate change (Clark *et al.*, 2016). It is for this reason that uncertainty has dominated the developed of the coupled modelling framework presented in this thesis. This section outlines the steps taken to minimise uncertainty in the component models; how the end-user can further contribute to this; and the additional uncertainty introduced through the use of climate projections. The uncertainty introduced at each stage (Figure 1-4) is considered. For further definitions of these sources of uncertainty, see *Chapter 1 – 2. State-of-the-art.*

1.1 STAGE 1 – DEVELOPMENT OF A HYDROECOLOGICAL MODEL

In this thesis, the first step in the refinement of the hydroecological modelling approach was the consideration of potential delays in hydroecological response through the addition of time-offset hydrological indicators. The validation highlighted that this phenomenon may manifest across a range of flow regime groups. In capturing this additional information, a source of unquantifiable epistemic uncertainty is removed.

In the development of a hydroecological model, the first type of uncertainty introduced is sampling and measurement error. The controls available to reduce such uncertainty are necessarily case study specific: (1) the use of ecological data which follows a standardised methodology, for example, in the UK since 1992, macroinvertebrate sampling follows the Environment Agency's standard semi-quantitative protocol (Murray-Bligh, 1999); the use of flow data which is subject to quality control checks. To ensure the temporal transposability of the model, the length of the observed time series should, ideally, cover a range of climatic periods (wet/dry) (Klemeš, 1986).The ability to achieve this control is complicated by the limited availability of macroinvertebrate data (Monk *et al.*, 2006).

Structural and parameter uncertainty is introduced through model selection and parameterisation. A review of the literature (in *Chapter 3. Hydroecological modelling*) highlighted that the hydroecological modelling community has largely ignored this source of uncertainty. The principal focus has been on addressing parameter redundancy, typically through Principal Component Analysis. This framework introduces a number of controls through the use of the information theory approach.

The information theory approach was applied using the R package *glmulti* (Calcagno, 2013). The package uses a genetic algorithm to increase the probability of identifying the model global optimum (Calcagno and de Mazancourt, 2010). The genetic algorithm evaluates candidate models based on statistical properties – the second order bias corrected Akaike Information Criterion (after Burnham and Anderson (2002)). A multi-model average is based on a subset of the best performing candidate models. By not focussing on a single best model, equifinality, i.e. that there exist a number of equally plausible models, is acknowledged. The parameters included in the hydroecological multi-model average are those which are identified as ecologically relevant hydrological indicators for the specific catchment. The unique selling point of the information theory approach is that these indices are ranked by their weight of supporting evidence. This importance can in turn be used to inform the parameterisation of the hydrological modelling without the addition of user bias.

1.2 STAGE 2 – DEVELOPMENT OF A HYDROLOGICAL MODEL

Previous hydrological modelling approaches for the replication of ecologically relevant hydrological indicators (ER HIs) have been subject to high levels of uncertainty (see *Chapter 4. Hydrological modelling*). Thus, stage 2 of the coupled modelling framework introduces a number of controls for minimising this.

With regards to the hydroecological model, ensuring that the observed flow and climatic data have been subject to sufficient quality control is essential to minimise measurement error. As stated prior, the length of the time series should cover a range of climatic periods, a more achievable goal when pairing with ecological data is not necessary. By merit of not relying on goodness-of-fit statistics (as part of an objective function) to parameterise the hydrological model, the modified covariance approach minimises the impact of disinformative data (Vogel and Sankarasubramanian, 2003).

The modified covariance approach is novel in its focus on model validation prior to the parameterisation of the model. The hydrological model structure is rejected if the observed and simulated moments do not coincide, thereby eliminating the structural uncertainty associated with using an inapt model for the given catchment. For example, for the case study applications in chapter 4, it was shown that the 6-parameter GRJ model variant was not fit for purpose. This is not dissimilar to Vogel and Sankarasubramanian's (2003) demonstration of the potential of model error introduced into the *abc* model to *"confuse us into thinking a model is acceptable, when in fact it is not"* (p. 7-3).

Parameter uncertainty by focussing on replicating the essential characteristics of the catchment rather than the time series. Instead of using a goodness-of-fit statistic to evaluate the performance of the candidate models, a limit of acceptability (maximum error threshold) is defined for each index. It is thus possible to identify the plausible parameter space where the error associated with the most important indicators is minimised. Those less important, may then be safely deemed of secondary concern given their lesser influence over the hydroecological relationship. Thus informed, the flow projection outputs from the hydrological model can be said to be less uncertain than an alternative approach which does not explicitly account for ER HI importance in this targeted way.

Equifinality represents an additional source of parameter uncertainty. By focussing on identifying a plausible parameter space, the modified covariance approach allows for the consideration of a range of parameter sets. Thus, the ER HI projections represent a range of values. The capacity to report such ranges, is in itself, a benefit, conveying the innate uncertainty of these values to the end user.

1.3 STAGE 3 - CLIMATE PROJECTIONS

In the third stage of the framework, the two component models are coupled and run in simulation mode (Figure 1-4). The input data is in the form of climate change projections. These are long-term projections of climate change up to the end of the 21st century and beyond. A projection is not a forecast: they are highly uncertain. In the Intergovernmental Panel on Climate Change's (IPCC) fifth assessment report, Collins *et al.* (2013) cite three reasons for this uncertainty: (1) future anthropogenic and natural emissions represent an unknown, it is not certain what trajectory or for this will take; (2) epistemic uncertainty, due to *"incomplete understanding and imprecise models of the climate system"* (p. 1034); and (3) natural climate variability. The climate projections thus introduce significant uncertainty to the framework and subsequent projections of hydroecological response. This section provides a brief overview of where opportunities lie in the decision-making to minimise this uncertainty.

First and foremost, the projections used must match the input requirements of the hydrological model in terms of the input climate variables and the time step. For example, the GR suite of models considered in the case study applications would require projections at a daily timestep of precipitation and temperature (from which potential evapotranspiration may be derived).

Typically, climate change impact studies consider 30-year time slices to allow for comparison with the standard World Meteorological Organisation's 30-year climate normal (Arguez and Vose, 2010); for the purposes of uncertainty, this is not strictly necessary. However, statistically speaking, the time series should be of sufficient length to allow for meaningful conclusions to be made. Thus, a 30-year period can be considered a useful minimum guideline.

In order to reduce uncertainty associated with the climate models, an ensemble of climate projections should be used. Flato *et al.* (2013) describe two types of climate ensemble, each accounting for a different source of uncertainty: the multi-model ensemble (MME) and the perturbed physics ensemble (PPE; also known as a perturbed parameter ensemble). An MME considers a number of climate models, thereby allowing for an estimate of structural uncertainty, whilst the PPE explores parametric uncertainty in a single climate model through systematic variation of uncertain model parameters. There is no guidance on which is most appropriate in practice; computational demand is a limiting factor in the consideration of multi-model perturbed physics ensembles. In the third IPCC assessment report (Moore *et al.*, 2001), the need to consider the sensitivity of global climate models to parameterisation and parameter sets was highlighted. In response, the last two generations of UK climate projections (UKCP) from the Met Office Hadley Centre, UKCP09 and UKCP18, have been PPEs (Collins *et al.*, 2011).

Natural climatic variability allows low probability climatic events to be captured more effectively (Schlabing *et al*., 2014), which is particularly important for ecosystems (Wigley, 1985). The associated uncertainty may be reduced by increasing the number of realisations, e.g. through the use of a weather generator, improves this even further (Schlabing *et al.*, 2014). Projections in the form of change factors, for example the main product output of UKCP09, should not be used; change factors are applied to baseline observations and therefore are not able to capture any change in climatic variability.

2. FOREWORD

The fourth publication serves to bring the framework together (objective 3.2) and provides the necessary validation and demonstration of the framework in practice within the principal case study, the River Nar (objective 3.3). This foreword sets the scene for the publication, providing an overview of both the climate projections used in the case study application as well as the validation methodology.

2.1 CASE STUDY APPLICATION

The framework is validated and demonstrated with reference to UKCP09. The UKCP09 climate projections are probabilistic in nature, being derived from a PPE of the Hadley Centre Coupled Model version 3 (HadCM3). In an attempt to account for structural bias, UKCP09 introduces a proxy correction based on a further 12 climate models from the World Climate Research Programme's (WCRP) third generation Coupled Model Intercomparison Project (CMIP3) (Murphy *et al.*, 2009). The projections are forced by three equally plausible emissions scenarios from the IPCC special report on emissions scenarios (SRES) (Nakićenović *et al.*, 2000): low, B1; medium, A1B; and high, A1FI. The case study application uses the weather generator product (Jones *et al.*, 2010) which provides synthetic stochastic time series of climate variables (based on observed climate statistics) at a daily time step on a 5 km grid.

Murphy *et al.* (2009) identify three major sources of uncertainty in the UKCP09 climate projections: epistemic & scenario uncertainty and internal climate variability. The publication includes discussion of the controls in place to minimise this uncertainty.

Following the extraction of the data, the baseline (from the weather generator) and observed climate were compared (as recommended in Murphy *et al.* (2011)). For each climate variable, bimonthly and seasonal plots of the mean and 95% confidence intervals were produced. Where there was a lack of agreement, linear bias correction was applied (also bi-monthly).

The author recognises that the UKCP09 projections have been subject to criticism (for example see Charlton and Arnell (2014), Green and Weatherhead (2014) and Frigg *et al.* (2015a). However, it is worth reiterating that the aim is to validate and demonstrate the use of the framework, with any determination of the impacts out with the scope of this thesis; some discussion of the impacts across three time slices and the three emissions scenarios is, however, available in Visser *et al.* (2019a) *(Appendix B)*. In addition, these projections have now been superseded by the next generation of emissions scenarios and climate models (CMIP5) and should be considered outdated. At the time of analysis (2016/2017), UKCP09 represented the best data source available for UK climate projections; delays in the publication of the UKCP18 meant that it was not viable for consideration.

2.2 VALIDATION

Chapters 3 and 4 looked to the development of methods for deriving the component models which form stages 1 and 2 of the framework. Using observed hydroecological and hydroclimatological datasets, the use of these approaches was validated and demonstrated through application to a number of case study locations. Validated as standalone models only, it remains necessary to validate the coupled model in order to evidence the framework's practicability.

The framework and coupled model are validated using climate projections on the baseline period (1961-1990). For demonstrative purposes, all 10,000 variants of the UKCP09 weather generator were considered. Following Murphy *et al.* (2011), the weather generator projections were linearly bias corrected (rescaling of standard deviation and mean), where necessary, at a bi-monthly time step prior to use. The baseline climate projections serve as the input to the hydrological model. The simulated ER HIs are then input to the hydroecological model and the outputs compared with observations. The 10,000 realisations from both models are validated against observed data. With this resulting range of variants, the projections are considered to be validated if the observations lie within their centres.

The framework assumes that the relationship underpinning the coupled model is stationary – that is, that it will hold under different climate realisations. It is thus necessary to validate the coupled model's transposability. By use of a weather generator, this is already, partially, achieved through the baseline validation. The generator provides multiple realisations of climate which could have occurred. Thus, if the hydroecological projections made are intelligible and lie within the established realms of possibility, the transposability of the coupled model is confirmed.

3. PUBLICATION 4

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For errata, see Appendix C, C-3.

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A coupled modelling framework to assess the hydroecological impact of climate change

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ABSTRACT

Rivers are among the ecosystems most sensitive to climate change. Whilst methods quantifying the impact and uncertainty of climate change on flow regime are well-established, the impact on hydroecological response is not well understood. Typically, investigative methods are qualitative in nature or follow quantitative methods of limited scope, whilst the effect of uncertainty is frequently minimised. This paper proposes a coupled hydrological and hydroecological modelling framework to assess the impact of climate change on hydroecological response quantitatively. The characterisation and reduction of modelling uncertainties was critical to the development of the framework. The ability of the framework is illustrated through application to a case study river, the River Nar, Norfolk, England, using the UKCP09 probabilistic climate projections (high emissions scenario, SRES A1F1). The results show that, by the 2050s, a reduction in instream biodiversity is *virtually certain* if future emissions follow the assumptions of SRES A1F1. Disruption to the natural low flow processes, essential to ecosystem functioning, is also indicated. These findings highlight the importance of the framework in water resources adaptation, particularly with respect to future environmental flows management.

1. Introduction

The global climate system is changing, with changes to climatic behaviour (mean and variability) projected beyond the 21st century (IPCC, 2014). Climate change is expected to amplify existing pressures on natural resources, as well as create new ones (IPCC, 2012). Amongst these, freshwater is considered the most essential (Vörösmarty et al., 2010); rivers and their ecosystems provide a diverse range of services upon which humans are dependent (Yeakley et al., 2016), these include: fresh water supply for human consumption; hydro-hazard regulation; and water purification (Gilvear et al., 2017). It is thus through freshwater resources, particularly rivers, that some of the most significant impacts of climate change will be felt (Ostfeld et al., 2012). Consequently, there are significant questions over the long-term sustainability of water resources (Gleick, 1998, 2016; Klaar et al., 2014). It is clear that effective water management is central to successful climate change adaption (Ostfeld et al., 2012).

Climate is a major determinant of hydrological processes, where precipitation, temperature and evaporation represent the dominant drivers (IPCC, 2007). Consequently, a changing climate will inevitably lead to alterations of river flow regimes (Rahel and Olden, 2008; Arnell and Gosling, 2016). Attempts to model the impact of climate change on water resources have been ongoing since the mid-1980s (Arnell and Reynard, 1996; Christierson et al., 2012).

Climate projections are, however, subject to large unquantified uncertainties (Murphy et al., 2004), leading to concerns over their suitability for water resources adaptation and planning (Kundzewicz et al., 2008; Wilby, 2016). Examples of these uncertainties include (Clark et al., 2016; Wilby, 2016): (1) epistemic uncertainty, the inability to properly capture the underlying processes and feedbacks; and (2) accounting for variation due to natural climatic variability. In practice, uncertainty dictates the usefulness of the model. Inaccurate appreciation of this uncertainty precludes meaningful interpretation of the model, leading to sub-optimal decision-making (Warmink et al., 2010) when considering future projections. Clark et al. (2016) posit that, research which focuses on characterising, reducing and representing (quantifying) these uncertainties may allow for the provision of plausible flow projections under climate change. Difficulties with regards to the quantification of climate uncertainty may be addressed through the use of a perturbed physics ensemble: an ensemble of GCMs where variation of the model parameters allows quantification of uncertainty (Murphy et al., 2004; Clark et al., 2016). Such enhanced projections have been available for the UK since 2009 through UKCP09.

Variability in the flow regime is widely acknowledged as the major

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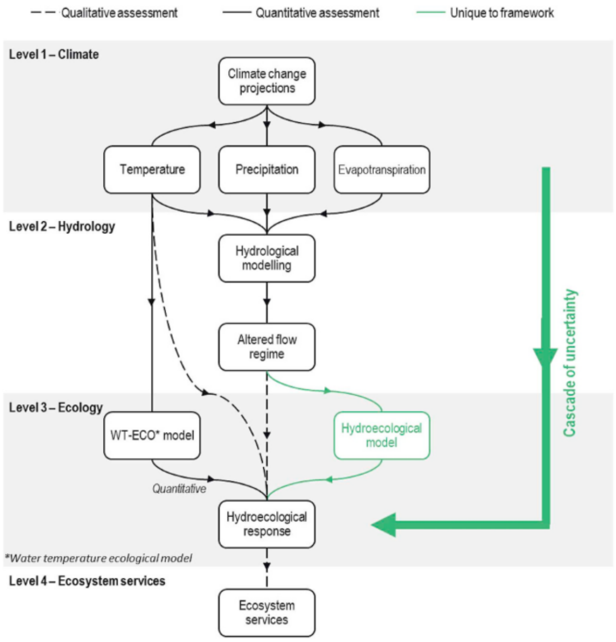

Fig. 1. Pathways through which the impacts of climate change on hydroecological response have been considered. Green indicates aspects which are unique to the proposed coupled modelling framework. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

determinant of ecological health in riverine ecosystems (e.g. Power et al., 1995; Lytle and Poff, 2004; Arthington et al., 2006). Alteration of this natural flow regime threatens the ability to provide ecosystem services (Rahel and Olden, 2008; Vörösmarty et al., 2010; Arthington, 2012). Despite this, and perhaps surprisingly, the effects of climate change on river health are rarely considered, as observed in Durance and Ormerod (2007). Seven years later, Schlabing et al. (2014) describes little change, noting that even when accounted for, the methodology employed is often over simplified and rudimentary. A brief review of such work performed over the last two decades is thus indicated (see also Fig. 1).

A large number of the studies investigating the impact of climate change on hydroecological response have been qualitative in nature (Fig. 1, level 1 to 3 directly; not pictured); examples include Meyer et al. (1999); Ostfeld et al. (2012); Filipe et al. (2013) and Death et al. (2015). Whilst the number of quantitative studies has increased, their scope is often limited to the direct links between climate (temperature) and hydroecological response (Fig. 1; for example, Durance and Ormerod, 2007; Kupisch et al., 2012 and Jyväsjärvi et al., 2015). In these studies, the impact of the altered flow regime is not considered and rarely acknowledged.

Döll and Zhang (2010) were the first to consider the impact of climate change on the flow regime at a global-scale. Assessment of the hydroecological impacts was qualitative in nature, with limited consideration of changes in the number of endemic fish species (counts are not considered meaningful bioindicators; for example see Li et al., 2010). The authors acknowledge that quantitative estimates of ecosystem response "have not yet been derived". Following this, studies of a similar nature have been undertaken at higher resolutions (catchment level); examples include Tang et al. (2015); Hassanzadeh et al. (2017) and O'Keeffe et al. (2018). Advances have also been made in the assessment of direct climate change impacts on the provision of freshwater ecosystem services (see conceptual framework in Pham et al., 2019); though again these are, at present, qualitative in nature.

Merriam et al. (2017) perform a habitat assessment using a coupled stream temperature and hydrological model. Whilst the focus is on the availability of thermally suitable habitats for brook trout, and not flow alteration directly, the study represents an important advancement towards fully quantitative assessment of the instream ecological impacts of climate change. Nevertheless, significant questions arise as to the robustness of the applied methodology. The authors make assertions, using phraseology such as "high degree of certainty", when discussing results based upon R-squared values and RMSE, a statistical measure of average inaccuracy. Yet, the problems inherent to RMSE have been recognised for some three decades (Willmott et al., 1985), and more recently, Willmott and Matsuura (2005) conclude that, in the context of climate study, model-performance evaluations based primarily on RMSE are questionable and should be reconsidered. Further, issues arise in the calibration of the hydrologic model, where performance is assessed in terms of Nash-Sutcliffe, a statistic subject to long-standing, broad, and sustained criticism (Legates and McCabe, 1999; Seibert, 2001; Criss and Winston, 2008). Indeed, Clark et al. (2016) state that, when modelling the hydrological impacts of climate change, Nash-Sutcliffe (and similar efficiency criteria) introduces additional, unaccounted uncertainties. This disregard of uncertainty throughout the paper calls into question the validity of the results.

It is clear that methods to quantify the impact, and associated uncertainties, of climate change on the flow regime are well-established (Fig. 1, level 1 and 2). The hydroecological implications are less well understood and are rarely considered quantitatively; where attempts have been made, the effect of uncertainty is underplayed. Consequently, the impact of climate change on hydroecological response is unclear, and the fallout for ecosystem services poorly understood. This paper proposes a coupled hydrological and hydroecological modelling framework to assess the impact of climate change on hydroecological response quantitatively. The development of (each stage of) the framework has centred around the characterisation and reduction of uncertainty, in line with the recommendations in Clark et al. (2016). The outputs from this framework are quantitative hydroecological projections of climate change impacts. These outputs are intended to support water resources adaptation, for example in the equitable allocation of water for human use and the environment (known as environmental flows). In order to validate and demonstrate the ability of the framework, this paper features an application to a case study river, the River Nar in Norfolk, England.

2. Framework

An overview of the three main stages of the proposed framework is presented in Fig. 2. In stage 1, the hydroecological model is developed based on advances made in: (1) Visser et al. (2017), where lag in ecological response, an important component of flow variability (Monk et al., 2017), is accounted for through the consideration of multi-annual hydrological indicators; and (2) Visser et al. (2018a) present an information theory (IT) approach to minimise and quantify structural and parameter uncertainty. The second stage of the framework is the parameterisation of the hydroecological following a modified covariance approach (Visser et al., 2018b). The modified covariance approach focuses on the replication of specific hydrological characteristics (identified in stage 1), whilst also addressing a number of known limitations and uncertainties in hydrological modelling. In stage 3, climate projections serve as the input to the coupled model, providing the quantitative hydroecological projections of climate change impacts. Application of the framework to a case study river catchment is subsequently considered in 3. Case study application.

A holistic depiction of uncertainty was central to the development of the proposed framework. Additional commentary on the characterisation and reduction of the sources of uncertainty, following Clark et al. (2016), is provided in Appendix A.

In the development of this framework it is necessarily assumed that the hydroecological relationship remains stationary (as in

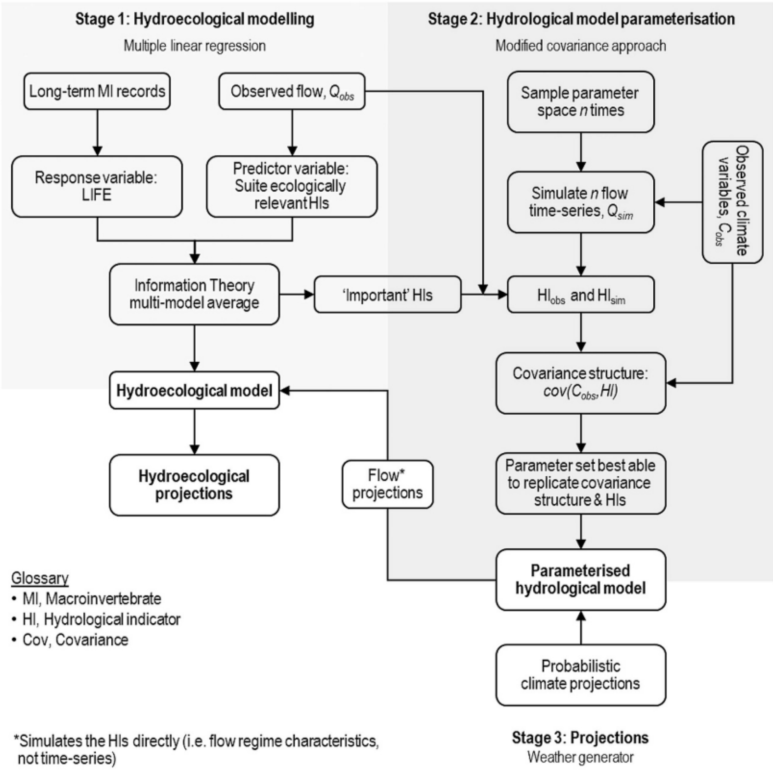

Fig. 2. The three stages of the proposed coupled modelling framework to quantitatively assess the hydroecological impact of climate change.

hydroclimatological modelling). The evolution of such relationships remains an unknown and is beyond the scope of this paper. A further important limiting factor of many hydroclimatological studies is the focus on extreme climatic events (e.g. Filipe et al., 2013; Thornton et al., 2014; Death et al., 2015). Climate models are well-known for their ineffective simulation of extreme climate, particularly with regards to precipitation (IPCC, 2014); knowledge of the impacts of extreme events is therefore limited. In an effort to address this, the UKCP09 climate projections distribution tails are clipped (5% and 95% probability levels; Murphy and Sexton, 2013). In addition, changes in climate mean and variability may lead to compound events or clustered multiple events; these events are not extreme in themselves but can lead to extreme events and/or impacts (IPCC, 2012). Essentially, severe impacts can occur from minor climatic events. The focus of the framework is therefore on these impacts rather than stochastic (individual extreme) events.

2.1. Stage 1 – hydroecological model

Statistical methods are well-established for the testing of hydroecological hypotheses, these include: multiple linear regression (for example, Clarke and Dunbar, 2005 and Monk et al., 2007), and multilevel models (recent examples include Bradley et al., 2017 and Chadd et al., 2017). Hydrological indicators (HIs) and ecological data serve as the basis for the development of these models. With their sensitivity to change, macroinvertebrates are ideal indicators of river health (Acreman et al., 2008; EA, 2013). This response is determined by considering macroinvertebrate flow velocity preferences as described by the Lotic-Invertebrate Index for Flow Evaluation (LIFE; Extence et al., 1999), a weighted index which takes into account the flow velocity preferences of the macroinvertebrate community; LIFE scores can range from one to twelve, indicating a preference for limited flow & standing water to rapid flows respectively.

2.1.1. Data

The structure of the benthic macroinvertebrate community is subject to change throughout the year. Typically, peaks of activity occur in spring (AMJ) and autumn (OND). Seasonal focus in hydroecological modelling is determined by factors such as the quantity and quality of the available data and the overall modelling objective. For example, fishing is vital to the communities along the case study river, the River Nar (Garbe et al., 2016). If the goal was to preserve future brown trout populations, then modelling efforts would seek to protect their primary food source, *Ephemeroptera baetidae* (mayfly), which hatch during the spring season. Macroinvertebrate data may be utilised at the species or family level; however, it should be noted that the use of family level data may mask species-specific information (Monk et al., 2012), leading to a reduction in accuracy (Extence et al., 1999).

A hydroecological dataset is created by pairing the ecological data with HIs. These indicators should be ecologically relevant, reflecting the five facets of the flow regime required to support the riverine ecosystem (Richter et al., 1996): magnitude, frequency, duration, timing and rate of change. To date, over 200 ecologically relevant hydrologic indices have been proposed (Olden and Poff, 2003; Monk et al., 2006; Thompson et al., 2013). Should seasonality be present in the hydrological regime, the time-series is split into relevant hydrological seasons; the HIs are then calculated for each. A number of studies (on groundwater-fed rivers) have observed a delay in macroinvertebrate response (for example, Boulton, 2003; Durance and Ormerod, 2007). Visser et al. (2017) and Visser et al. (2018a) propose the incorporation of time-offset HIs to account for this effect. The time-offset may require fine-tuning if the number of indicators cannot be sufficiently reduced in the steps below; beyond this, no additional work is required.

With a large number of HIs, both variable redundancy and computational effort represent significant challenges. In response, Principal Component Analysis (PCA) is applied, allowing only those indices which describe major aspects of the flow regime to be identified; following Olden and Poff (2003), the most relevant indices are selected proportionally from the five facets of the flow regime described above. The ecological data is then be paired with this set of ecologically relevant HIs.

2.1.2. Statistical modelling

As further aspects of hydroecological relationships are understood, such as ecological lag in response, the likelihood of modelling errors and uncertainty is increased. To account for this, the proposed framework makes use of an IT approach to determine the structure of the hydroecological model (after Visser et al., 2018a). The IT approach provides a robust measure of both structural and parameter uncertainty (see Appendix A.1) as well as a measure of the statistical importance of the model parameters (HIs; a central factor in the parameterisation of the hydrological model, stage 2).

The application of the IT approach consists of 4 steps; for a more detailed discussion see Appendix B.1 or Visser et al. (2018a). To summarise: (1) candidate models are evaluated with respect to the second-order bias corrected Akaike Information Criterion (AICc, equation (B1); after Burnham and Anderson, 2002); (2) a best approximating model is inferred from a weighted combination of all the candidate models; (3) the parameters are ranked, such that the highest value (Akaike weight, equation (B3)) represents the most important in the model; (4) measures of uncertainty (structural and parameter) are made.

In the development and application of the framework, the IT approach was applied using the R package *glmulti* (Calcagno, 2013), developed and applied in a relevant discipline (see Isbell et al., 2011). In *glmulti*, a genetic algorithm (GA), a type of optimisation that mimics biological evolution, is used to select a subset of models (each assessed based on the above IT approach). The GA incorporates an immigration operator, allowing removed HIs to be reconsidered. Immigration sees the level of randomisation increase, and hence the likelihood of model convergence on the global optima rather than some local optima (Calcagno and de Mazancourt, 2010). Inference from a consensus of 5 replicate GA runs has been shown to greatly improve convergence (Calcagno and de Mazancourt, 2010). The multi-model average is subsequently derived from this subset of models. Parameters where the estimate and confidence intervals are zero (i.e. certainty that the index is not to be included), are then removed. In line with Anderson (2007), the set of model parameters is reduced to those accounting for 95% of the cumulative information (see Appendix B.2).

For validation of the hydroecological model see Appendix C.2.

2.2. Stage 2 – hydrological model

The HIs identified in stage 1 represent those characteristics of the flow regime which dominate ecological response. Driven by climate projections (Fig. 2), changes to these HIs may be determined from flow time-series simulated via hydrological model. Climate projections, input to the coupled hydrological and hydroecological model, allow the impacts of climate change on hydroecological response to be determined quantitatively (stage 3). This second stage of the proposed framework focusses on the parameterisation of the hydrological model.

Clark et al. (2016) highlight model parameterisation as a major source of uncertainty. Typically, hydrological models are parameterised following a split-sample calibration-validation approach, with calibration focussing on the goodness-of-fit between observed and simulated flow. Limitations of the approach are widely acknowledged, these include (Westerberg et al., 2011; Clark et al., 2016): (1) bias in the model parametrisation as the result of disinformative data (Pelletier, 1988; Montanari et al., 2013); (2) the arbitrary nature of GOF statistics; and (3) equifinality (Beven, 2006).

In this proposed framework, the modified covariance approach (Visser et al., 2018b), based on Vogel and Sankarasubramanian (2003), is applied in an attempt to address these limitations (see also Appendix A.1). In Visser et al., 2018b, comparison relative to studies with similar modelling objectives (the simulation of ecologically relevant HIs) showed improvement in both model performance and consistency. A further major advantage of the approach lies in the focus on identifying the region of parameter space which best captures the characteristics of the HIs, providing a greater understanding of model suitability, limitations and uncertainty.

2.2.1. Hydrological model

To further minimise uncertainty, a parsimonious lumped hydrological model should be selected. In the development of the framework, the daily models from the GR (Génie Rural) suite of hydrological models were considered (GR4J, GR5J and GR6J; 4–6 free parameters). The GRJ models have been applied in a variety of hydrological contexts, examples include: Le Moine et al. (2008); Perrin et al. (2008); Coron et al. (2012); Smith et al. (2012); Coron et al. (2017). With observed moments lying outwith the simulated moments (see section 2.2.2), the five and six-parameter models GR5J and GR6J were rejected.

Continuous (daily) time-series of flow, precipitation and potential evapotranspiration serve as model input. The time-series should be of sufficient length for validation on the climate baseline in stage 3 (for example, the UKCP09 baseline is 1961–1990).

2.2.2. Modified covariance approach

The hydrological model is parameterised following the modified covariance approach, as set out in Visser et al. (2018b). In using this approach, the modelling objective is not the replication of a flow time-series, rather, it is the identification of the region of parameter space which is best able to replicate the HIs. For a more extensive discussion of the modified covariance approach see Visser et al. (2018b).

In the application of this approach, the complete parameter space of the hydrological model is sampled. The number of parameter sets is dependent upon the number of free parameters and the level of uncertainty adjudged acceptable. To reduce bias, the parameter space should be sampled uniformly; for example, using Sobol quasi-random sequences (a Quasi-Monte Carlo method; Caflisch, 1998). The parameter sets thus established, the hydrological model is run in simulation mode using observed climate data. For each of the n time-series, the covariance (between observed climate and simulated flow) is calculated; this is repeated for the observed flow data. The HIs, identified in stage 1, are then determined from both the observed and simulated flows.

Prior to the selection of a parameter set, it is first necessary to validate the hydrological model structure. This is facilitated through plots of the observed and simulated relationships between the covariances and HIs. The model is validated if the moments agree, i.e. observed moments lie within the simulated moments (sampled parameter space). Error thresholds, in combination with index importance (determined in stage 1), are used to identify a suitable parameter set. A linear relationship between the minimum and maximum error thresholds and index importance is defined. Parameter sets which fall below this defined limit are rejected. For additional details see section 3, Case Study Application or Visser et al. (2018b).

The focus of the covariance approach is on the replication of specific hydrological characteristics in the catchment (the HIs), as opposed to flow. Consequently, the hydrological model should be assessed in terms of its ability to replicate these characteristics rather than the observed flow time-series. Indeed, the replication of the time-series is anticipated to be poor, consistent with similar work focussed on the replication of catchment characteristics (e.g. see Seibert, 2000).

2.3. Stage 3 – projections

2.3.1. UKCP09 weather generator

The UKCP09 Weather Generator (WG) was selected due to its ability to represent natural (climatic) variability (Murphy et al., 2009; Kay and Jones, 2012). This consideration of natural variability allows extraordinary (low probability) climatic events to be captured more effectively (Schlabing et al., 2014), which is particularly important for ecosystems (Wigley, 1985). The WG creates synthetic stochastic time-series of climate variables based on observed climate statistics. The WG is perturbed to represent future climate through the application of change factors. Projections are at a 5 km resolution, allowing for representative simulation across smaller catchments (< 1000 km^2, typical in the UK; Kilsby et al., 2007; Jones et al., 2010). Data requests are submitted using the UKCP09 web-based portal (http://ukclimateprojections-ui.metoffice.gov.uk/ui/admin/login.php). The climate variables of interest are precipitation and potential evapotranspiration; note that, potential evapotranspiration may also be computed from the hourly time-series. The CMIP4 SRES scenarios upon which UKCP09 was based does not assign probabilities to specific emissions scenarios (Wigley and Raper, 2001; Meehl et al., 2007; Murphy et al., 2009); consequently, it is assumed that each emissions scenario is equally probable (Murphy et al., 2009).

For the validation of the WG output, UKCP09 recommend comparison of the observed and baseline climate data in the form of bi-monthly and seasonal plots of the mean and 95% confidence intervals (for each climate variable; DEFRA, 2011). To this end, linear bias correction is applied bi-monthly (where necessary).

2.3.2. Baseline validation

The baseline climate data is used to validate the framework. The generated climate variables are input into the hydrological model, generating a range of possible flow time-series; for each time-series, the important HIs are calculated (per hydrological year/season). These indices can be assessed relative to the observed indices (determined in Stage 2). Validation is through cumulative distribution and probability density functions (CDF and PDF respectively), comparison of the mean and 95% confidence intervals.

With these indices and the hydroecological model, a range of possible LIFE scores for the baseline period may be determined; validation is as above. If the length of the ecological time-series is insufficient, an alternative approach may be applied; this is further considered in the application of the framework.

2.3.3. Future hydroecological projections

Simulation of future hydroecological projections (LIFE) is analogous to the validation, with the exception that the future climate projections serve as the input data. Each emissions scenario/time-period should be considered distinct.

3. Case study application

The ability of the framework is both validated and demonstrated through application to a UK case study river. Descriptions focus on the case study specific data acquisition and preparation, the subsequent analysis being as per the described framework.

3.1. Study area

The Nar represents a vulnerable and important river type (groundwater-fed chalk stream), already subject to significant stress (NRT, 2012). The additional threat of climate change to its ecological potential cannot be understated. It is intended that the power of this new proposed framework be illustrated in its application to this case study river.

The spring-fed River Nar rises in the Norfolk chalk hills (52.749°N, 0.812°E), 60 m above sea level, flowing west for 42 km before joining the River Great Ouse (52.748°N, 0.394°E). The formation of the fen basin, and resultant dissection of the chalk, created two distinct river units, delineated by a significant gradient change at Narborough (Fig. 3; Sear et al. (2005)). With a greater abundance and quality of ecological data (Visser, 2015), the focus is on the 153.3 km^2 chalk sub-catchment.

The hydrology of the River Nar is characteristic of pure chalk streams (Sear et al., 1999), with a high Base Flow Index (0.91; Sear et al., 2005) and relatively low flows: mean 1.12 m^3/s, Q10 2.03 m^3/s and Q90 0.49 m^3/s over the available record, where Q10 and Q90 represent the 10% and 90% flow exceedance respectively (equivalent to 90th and 10th percentiles). A reliance on groundwater results in a highly seasonal flow regime, where aquifer recharge primarily occurs in winter months, leading to a progressive rise in river flow until March/April.

3.2. Stage 1 – hydroecological model

Routine macroinvertebrate sampling by the Environment Agency (and prior custodians) has been ongoing since 1985 (NRT, 2012); from 1992, the sampling methodology follows the Environment Agency's standard semi-quantitative protocol (see Murray-Bligh, 1999; data available upon request from the Environment Agency, 2018). Only samples identified to species level and collected in the spring season (AMJ; peak of macroinvertebrate activity) were considered. The LIFE scores were calculated for a total of seventy-two macroinvertebrate samples (1993–2012).

Hydrological data was extracted from the National River Flow Archive (1990–2012; CEH, 2018) at the Marham gauge (52.678°N, 0.548°E; Fig. 3). The hydrological data was subdivided into six subsets: two hydrological seasons, winter (ONDJFM) and summer (AMJJAS) and three time-offsets (0–2 years). A total of 63×6 ecologically relevant HIs were considered; this was reduced to 29 through PCA. This reduced set of HIs were then paired with the LIFE scores to create the hydroecological dataset.

3.3. Stage 2 – hydrological model

For parameterisation of the hydrological model, 54 years of daily average flow recorded at the Marham gauge were extracted (September 1961 to 2015). The corresponding climate variables were computed from daily average rainfall and hourly temperature data at 5 MIDAS stations in and around the catchment (Fig. 3; Met Office, 2016). The parameters of interest are the average daily precipitation (P) and potential evapotranspiration (PE); P is determined via the computation of the daily catchment average rainfall, whilst PE is estimated from hourly temperature data using the temperature-based PE model from Oudin et al. (2005).

In order to verify the method of investigation, $n = 100{,}000$ parameter sets were generated using Sobol sequencing. The HIs used to parameterise the model are those indicated by the hydroecological model in stage 1.

In the parameterisation of the hydrological model, the minimum and maximum error were specified as 17.5% and 35% ($2 \times error_{min}$) respectively, from which the linear threshold was determined (the relationship between the minimum and maximum allowable error and the relative importance of the variables; covariances were assigned a relative importance of 1).

3.4. Stage 3 – projections

To address a number of the uncertainties indicated in the introduction (see also Appendix A.2), the UKCP09 probabilistic climate projections are used. The 2050s (2040–2069) high emissions scenario (A1F1 SRES) is considered. This emissions scenario is approximately equivalent to a change in temperature of 4.3 °C by 2081–2100 (relative to the pre-industrial period 1850–1900; Riahi et al., 2011; Met Office, 2018b). For demonstrative purposes, the UKCP09 WG was run for the full range of 10,000 variants.

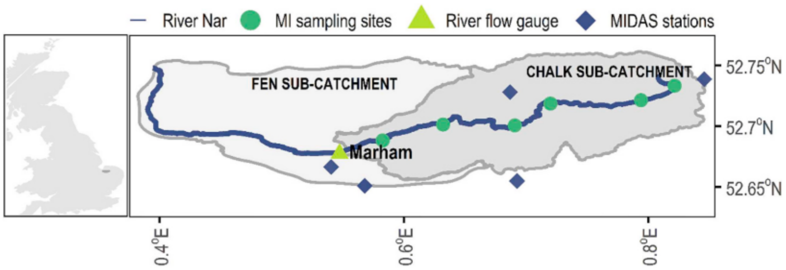

Fig. 3. River Nar catchment. Data sampling and recording sites/stations are marked; climate data is recorded at the MIDAS stations. **Inset:** Location of the River Nar in the UK.

Table 1
The HIs indicated in the hydroecological model in descending order of importance. The facets of the flow regime are denoted as M (magnitude) and R (rate of change); the hydrological seasons are indicated by W (winter) and S (summer).

Facet	Season & time-offset	Index name	Description	Unit	Importance	Relative parameter uncertainty
–	–	Intercept	–	–	1.00	0.39
M	W-0	10R90Log	Ratio of log-transformed low to high flows: log (P10)/log (P90). Log-transformation represents the log-normal distribution of flow.	–	0.86	1.29
R	S-1	revPos	Number of days when flow is increasing (positive reversals).	days	0.80	1.00
M	S-0	Q80Q50	Characterisation of moderate low flows; Q80 relative to the median.	–	0.51	2.40
M	S-1	logQVar	Variance in log flows.	m^3s^{-1}	0.37	2.96
M	S-1	Q90Q50	Characterisation of low flows; Q90 relative to the median.	–	0.19	3.47
M	S-1	Q70Q50	Characterisation of moderate low flows; Q70 relative to the median.	–	0.09	4.18
R	W-0	riseMn	Mean rise rate in flow.	m^3s^{-1}	0.07	6.43

4. Results and discussion

4.1. Stage 1 – hydroecological model

The hydroecological model, a linear multi-model average, is depicted in Equation (1) (overleaf). Summaries of the HIs are provided in Table 1; importance represents the relative weight of evidence in support of each index in the model (according to IT), whilst the relative parameter uncertainty is the 95% confidence interval relative to the parameter estimate. The underlying hydroecological processes are first considered, followed by a review of the predictive ability and uncertainty associated with the hydroecological model.

$$\begin{aligned} LIFE = {} & 0.07\ 10R90Log_{w,\ t-0} + 0.07riseMn_{w,t-0} + 0.93\ Q80Q50_{s,\ t-0} \\ & + 0.02\ Q90Q50_{s,\ t-0} + 0.3\ Q90Q50_{s,t-1} + 0.11\ Q70Q50_{s,t-1} \\ & - 0.04\ RevPos_{s,t-1} - 0.5logQVar_{s,t-1} \end{aligned} \quad (1)$$

4.1.1. Underlying hydroecological processes

The winter hydrological season, when the chalk aquifer recharges, features both the most and least important HIs, *10R90*Log and *riseMn* respectively. The indicator *10R90Log*, ratio of low flows to high flows (10th to 90th percentiles), is described as an indicator of responsiveness (Richards, 1990). The log-scale of the index, coupled with its importance, means that there is scope for 10R90Log to dominate the hydroecological model, both positively and negatively. Fig. 4 clearly illustrates that large values of *10R90*Log correspond with the highest LIFE scores, and vice versa. It is only when *10R90*Log is small (~ 0) that the other six indices contribute to LIFE score. Varying high and low flows shows that the highest values of *10R90Log*, and hence LIFE, are achieved when high flows are medium-high ($0 < \exp(P90(\log(Q))) < 1$). Given the log-space, the scope for a negative impact ($\exp(P90(\log(Q))) > 1$) is large. Surprisingly then, whilst magnitude of flow is of importance for the recharge of the aquifer, higher winter flows may actually negatively impact the macroinvertebrate community. The negative sign of the HI *riseMn* indicates a preference for a low mean rise rate in winter flows. However, the low importance of the index (Table 1) sees it consistently contribute less than 2.5% to the LIFE score (Fig. 4).

In terms of hydrological season, the summer months (AMJJAS) dominate the hydroecological model. There is an indication that, in the summer months, consistency in flow (low range/variation) is preferred: (1) a sustained increase in flow (*RevPos*) sees a large negative impact on LIFE (importance = 0.80); (2) though not as important, *logQVar* similarly implicates large variation in flow; and (3) minimising the range between low and median flows (*Q70Q50, Q80Q50* and *Q90Q50*) has an increasing effect on LIFE.

Looking to Fig. 5, four out of the five summer HIs are lagged (S-1). Essentially, these indicators are influencing the health of the river two years in advance; should there be a bad summer, with lots of variation, the consequences could be severe. However, the presence of the *Q80Q50* indicator in the immediately preceding season gives some scope for improvement. However, it is also worth noting that the negative impacts of a 'bad summer' would only be felt if the value of the index *10R90*Log was low, whilst if *10R90*Log is largely positive or negative, the preceding summers are of limited importance.

In terms of management, it is clear that summer floods in particular could be detrimental to the health of the river; perhaps representing an argument for improving connections to flood plains. Similarly, extremely high winter flows may be harmful, indicating there may be scope to abstract and store waters during the winter months for use in summer. However, it is worth noting that negative impacts are also a necessary component of the proper ecosystem function; for example, they might act as a 'natural reset button' (Everard, 1996; Lake, 2003). Interestingly, the majority of the indices are dimensionless (with the exception of *logQVar* and *riseMn*), this allows for some scope for variation in flow without causing excessive damage; for instance, in summer, a need for increased abstraction need not necessarily be a detriment to river health (though this assumption ignores the other effects of decreased flow).

4.1.2. Predictive ability and uncertainty

The predictive ability of the model is first indicated by the relative parameter uncertainty (unconditional variance, or 95% CI, relative to

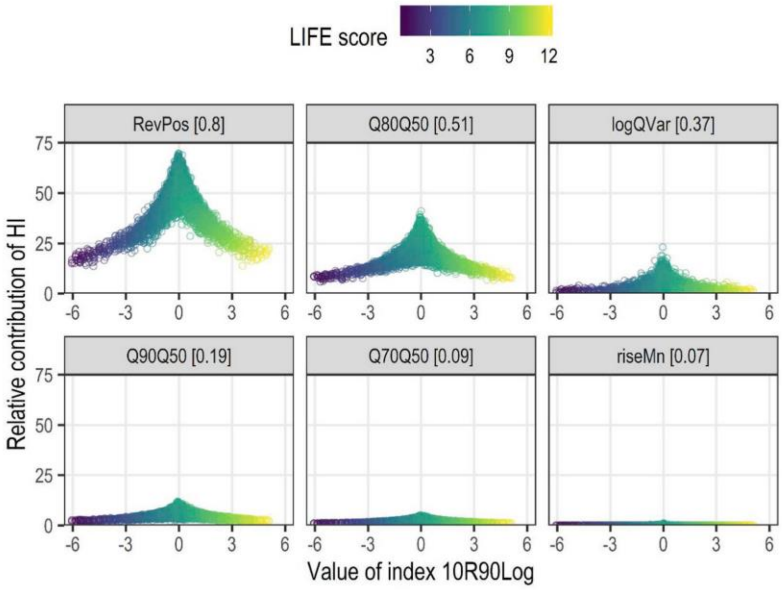

Fig. 4. Values of the index *10R90*Log vs the relative contribution of each of the HIs (see Appendix C.1) included in the hydroecological model (baseline projections, 1960–1990).

the parameter estimate; Table 1). Generally, as relative parameter uncertainty increases, the importance of the index decreases; this is one of the advantages of the weighting of the HIs in the IT approach (Visser et al., 2018a). The fact that the most important index, *10R90Log*, has greater uncertainty than the second most important, *RevPos*, suggests that this may be the best parameterisation possible in the model.

With regards to the implications of parameter uncertainty, further inference may be made through the consideration of the 10,000 Monte Carlo simulations (Fig. 6). The plot shows that the hydroecological model performs well (low interquartile range of 0.44 and relative error centred around one; perfect agreement). This level of uncertainty is considered satisfactory.

4.2. Stage 2 – hydrological model

Fig. 7 (a) depicts the observed and simulated relationship between the covariance of precipitation and flow, $\rho(P, Q)$, and the HI *Q80Q50*; Fig. 7 (b) depicts the same relationship for the climate variable potential evapotranspiration, $\rho(PE, Q)$. For all seven HIs, the observed moments lie within the simulated moments, validating the use of the hydrological model.

The capacities of the production (x1) and routing (x3) stores were estimated as 511 and 311 mm respectively; the time elapsed for flow routing is approximately 1.17 days (x2). Inflow from the chalk aquifer is represented by a positive groundwater exchange coefficient (x4) of 2.84 mm per day. The level of agreement for all seven HIs is summarised in Table 2. With a value of 0.8, the largest covariance relative error is for potential evapotranspiration; this is considered acceptable

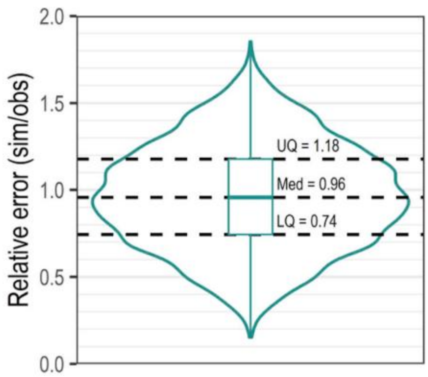

Fig. 6. Hydroecological model parameter uncertainty; distribution of the relative error for 10,000 MC simulations.

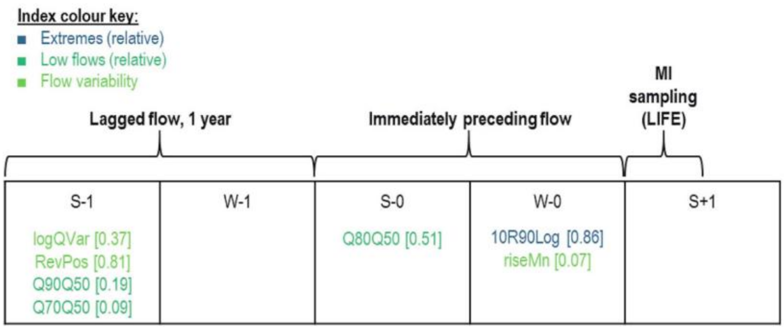

Fig. 5. Timeline indicating the impact of seasonality and timing on hydroecological response for the case study catchment. MI sampling occurs in spring. The hydrological seasons are indicated as W (winter) and S (summer).

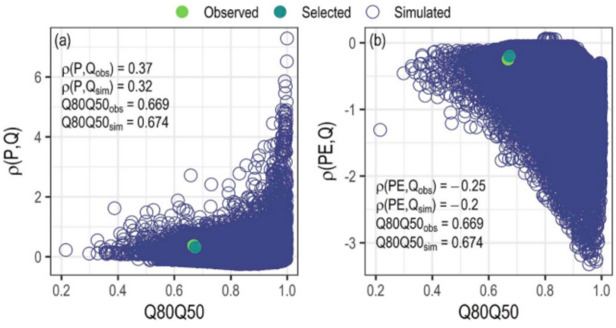

Fig. 7. Comparison of observed and simulated relationships covariance between **(a)** $\rho(P, Q)$, and the HI Q80Q50; and **(b)** $\rho(PE, Q)$, and the HI Q80Q50. The observed relationship and selected parameter set are highlighted.

Table 2
The level of agreement between the observed and simulated HIs.

Index	Importance	Observed	Simulated	Relative error
10R90Log	0.86	−0.822	−0.881	1.07; +7%
RevPos	0.8	1988	2156	1.08; +8%
Q80Q50	0.51	0.669	0.674	1.01; +1%
logQVar	0.37	0.426	0.408	0.96; −4%
Q90Q50	0.19	0.510	0.565	1.11; +11%
Q70Q50	0.09	0.776	0.770	0.99; −1%
riseMn	0.07	0.085	0.113	1.34; +34%

as precipitation is considered the principal determinant of flows in the East Anglia region (Kay et al., 2013). The HI relative errors are below ± 11%, with the exception of the least important index, *riseMn* (relative error = 34%). Overall, the level of relative error in the hydrological model is considered satisfactory; the impacts of the error in the index *riseMn* are likely negligible (based on the findings from the hydroecological model). For standard model validation, see Appendix C.3.

4.3. Stage 3 – projections

4.3.1. Baseline validation

The ability of the framework to reproduce the observed data, hydrological and hydroecological, is assessed via CDFs and PDFs. For the CDF plots, the observed function should situate within the boundaries of the baseline projections; ideally, centrally. The PDF plots focus on relative error, where a value of 1.0 indicates perfect agreement; here the objective is on a low interquartile range (IQR). In the interests of concision, validation of the hydrological projections centres on the index Q80Q50, selected both due to its high importance (0.80) and ease of interpretation (ratio of moderate low flows to median flows); summary tables for all seven HIs are available in Appendix C.4.

4.3.1.1. Hydrological model validation. The validation plots for the HI Q80Q50 are presented in Fig. 8. Fig. 8a/d are based on the UKCP09 baseline (1961–1990); both satisfy the objectives outlined above: the CDF of the observed values lies within the projections and the PDF shows a low IQR. Comparatively, the 95% confidence interval (CI) appears large, however, given the probabilistic nature of the projections this is not unexpected. The baseline interval for which ecological data is available (1986–1990) is summarised in Fig. 8b/e. The IQR is similar to the 30-year baseline, with a minor improvement in the 95% CI; given the limited time-period, the right-skew of the PDF (Fig. 8e) cannot be ascribed significance. On the alternative baseline (2010–2017), the CDF is notably stepped (Fig. 8c); this is reflected in the PDF (Fig. 8f) with a local maximum, and a median not equivalent to one (perfect agreement). Despite this, the IQR is the lowest of the three validation plots.

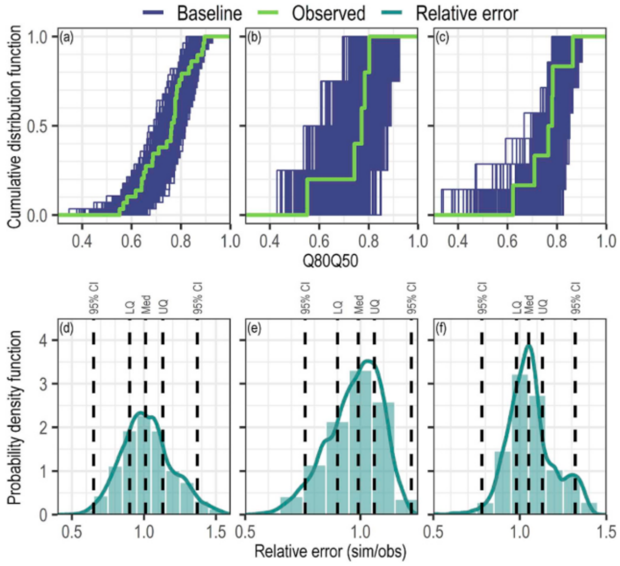

Fig. 8. Validation plots for the HI Q80Q50 on the baseline in its entirety (1961–1990; **left**); the baseline period for which there is corresponding ecological data (1986–1990; **middle**); and the alternative baseline (2010–2017; **right**).

Overall, for the CDF's, the observations lie centrally within the probabilistic projections, whilst the PDF's reveal low IQR's. The plots satisfactorily validate of the use of the UKCP09 projections through the hydrological model.

4.3.1.2. Coupled hydrological-hydroecological model validation. There is no ecological data (species LIFE) available for the period 1961–1990 (baseline validation period). However, sampling and identification of macroinvertebrates to the family level was carried out during the period 1989–1990, allowing for some comparison. To further address this, an alternative baseline was established through consideration of the earliest time-period considered by the UKCPO9 WG (2010–2039; reduced to 2010–2015), run for the medium emissions scenario for 1000 randomly sampled variants. Subsequently, the climate variables are bias corrected relative to the observed data in this period.

Validation plots for the hydroecological response, LIFE, as predicted by the coupled model, is presented in Fig. 9a/c for the baseline (1986–1990) and Fig. 9b/d for the alternative baseline (2010–2017); recall that for the period 1986–1990 only family LIFE data is available. On this baseline period, the CDF's (Fig. 9a) are in agreement, with a small IQR for the relative error of approximately 0.1 (Fig. 9c). The somewhat swollen 95% CI may have a threefold explanation: 1) family level application of the LIFE methodology tends to underestimate hydroecological response (Extence et al., 1999; Monk et al., 2012); 2) the limited number of years/data points; and 3) the probabilistic nature of the projections. For the alternative baseline (2010–2017), the CDF (Fig. 9b) is in agreement. The PDF (Fig. 9d) also reveals a lower IQR (relative to Fig. 9c) as well as an improved 95% CI.

Although the temporal range of the validation is limited, both time periods are able to achieve a satisfactory level of performance, thereby validating the use of the UKCP09 projections and the coupled hydrological-hydroecological model. The use of the coupled model is thus considered fit for purpose in application to future projections.

4.3.2. Future projections

The UKCP09 climate projections for the 2050s time slice of the high emissions scenario were inputted to the coupled hydrological and

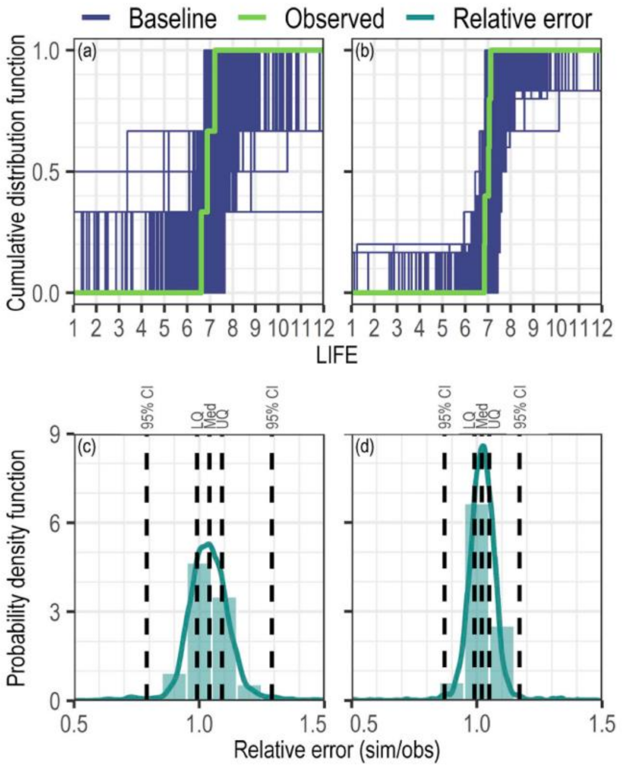

Fig. 9. Validation plots for hydroecological response based on a baseline period (1986–1990; **left**); and the alternative baseline (2010–2017; **right**).

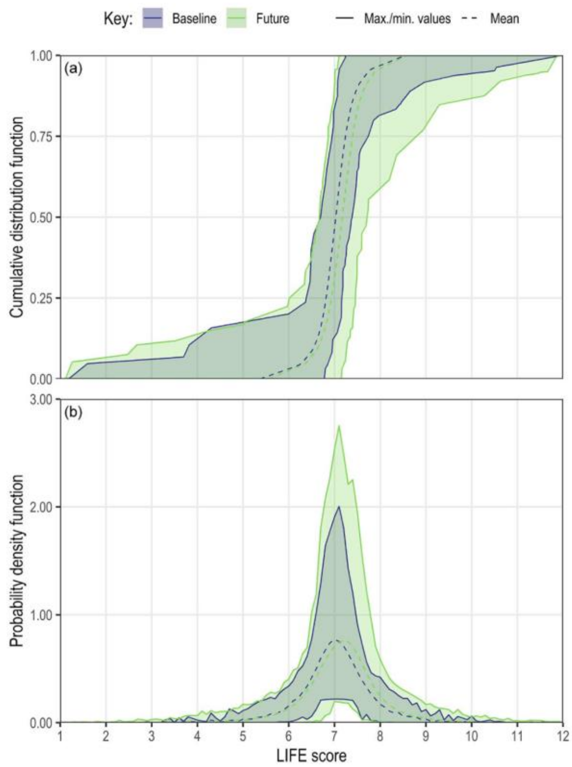

Fig. 10. Distribution of the future projections of hydroecological response, LIFE. Solid lines indicate the maximum and minimum values whilst the dashed lines represent the mean.

hydroecological model. The focus herein is on this hydroecological response. The projections of hydroecological response are first considered relative to the baseline through the CDFs and PDFs in Fig. 10.

Looking to the means first (dashed lines), the projected change is relatively small, however, there is a consistent increase in the range of possible LIFE scores across the distribution. The increase in maximum LIFE scores appears responsible for the majority of this change, though, some may also be attributes to the minimum values, specifically, the tails of the distribution (percentile < 0.375). In Fig. 4 it was shown that the index *10R90Log* was the main determinant of higher LIFE scores; it can thus be presumed that from percentile > 0.75, the increase in LIFE scores is the result of an increased stability in the ratio of high to low flows in the winter season. Where percentile < 0.75, the five summer HIs are likely to dominate, a further indication of increased stability of flows in the river.

Fig. 11 gives an indication of the probability of these hydroecological projections. These probabilities are in line with calibrated language used by the IPCC since AR4 (Treut et al., 2007; Mastrandrea et al., 2010, Table 3). Widening the confidence interval, from *about as likely as not* to *virtually certain* increases likelihood but results in a wider estimate. Overall, the bounds of uncertainty are relatively narrow, however, it is clear that the greatest confidence lies in the interquartile range, rather than the tails of the distribution. It should also be noted that, whilst the change to maximum LIFE scores is still in evidence, the decrease in LIFE scores at the lower distribution has disappeared, indicating a lack of certainty in those projections.

Whilst Schlabing et al. (2014) also observed limited changes in the central tendencies, they also note that it is important to consider the tails of the distribution. Although these events lie outwith the probabilities indicated in Fig. 11, this may be justified due to the ability of the WG to capture low-frequency events (Dubrovský et al., 2004; Mehrotra and Sharma, 2007). As in Schlabing et al. (2014), Fig. 12 looks to the hydroecological response at the 5th and 95th percentiles. It is important to note that LIFE scores at these percentiles will be primarily determined through the winter HI *10R90Log*.

At the 5th percentile, LIFE scores < 4.5 account for only 0.016% of observations and are therefore omitted. Broadly speaking, the frequency of lower LIFE scores appears to decrease under the future projections. Consequently, there is almost a 10% increase in the number of LIFE scores equal to 7. For the 95th percentile, LIFE scores > 9.5 account for 0.0244% of the total observations and are therefore omitted. With a marked increase in the frequency of LIFE ≥ 8, the positive change in hydroecological response previously observed (Figs. 10 and 11) is clearly in evidence.

4.4. Implications for the case study river

The proposed framework has indicated a clear hydroecological response to the projected changed climate under the A1F1 high emissions scenario in the 2050s. However, the magnitude and direction of change is projected to be both small and positive. The scale of this change is in line with the UKCP09 projections for the East Anglia region under this scenario. In this region, the projected change in mean annual precipitation is small, ranging from $\pm$ 5% across the 10th to 90th percentiles (Met Office, 2018); note that Kay et al. (2013) observe that hydrological response in East Anglia is principally determined by precipitation. Further, the range of LIFE values is known to be small,

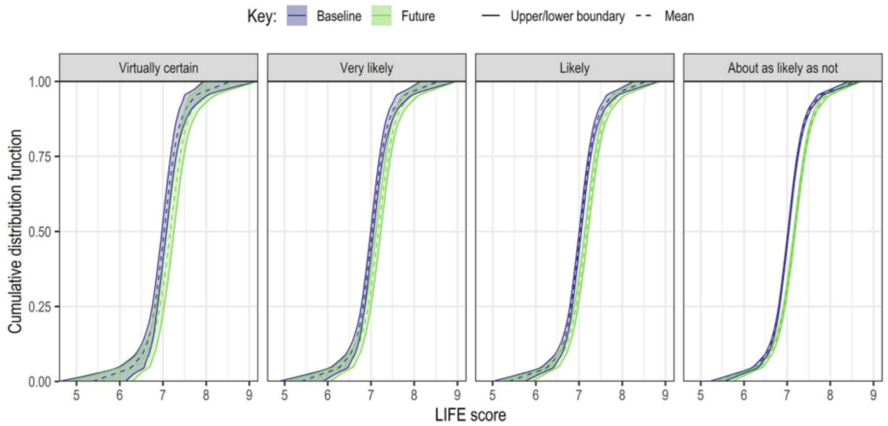

Fig. 11. Projections of hydroecological response bounded by the IPCC likelihood confidence intervals set out in Table 3.

Table 3
Uncertainty terminology as used by the IPCC (Treut et al., 2007; Mastrandrea et al., 2010); the third column indicates the confidence interval specified in this study.

Term	Likelihood	Specified CI
Virtually certain	99–100% probability	99.5%
Very likely	90–100% probability	95%
Likely	66–100% probability	85%
About as likely as not	33–66% probability	50%

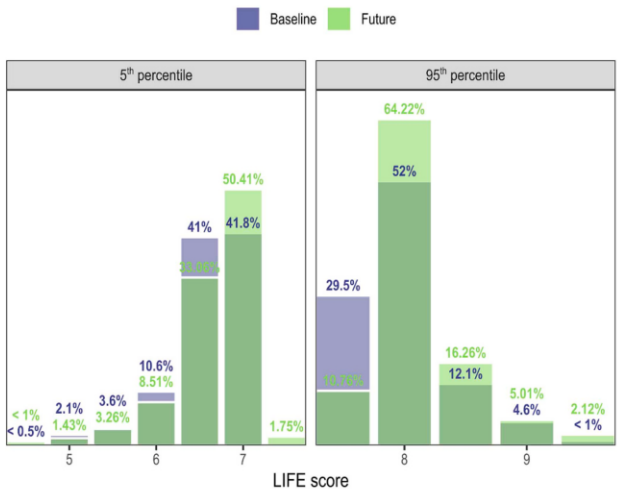

Fig. 12. Percentage distribution of LIFE scores at the 5th and 95th percentiles. LIFE scores < 4.5 and > 9.5 are omitted due to the low frequency of occurrence (discussed in-text).

particularly in the IQR (based on the BIOSYS database of ecological data across 548 catchments in England (Environment Agency, 2018), the IQR for 546 catchments is ≤ 1). Therefore, the observed change signal may be presumed to represent a true change in community structure.

Figs. 10 and 11 indicated a clustering of LIFE scores; visually this is most clear with the 1.375 increase in the mode (Fig. 10b). This is reflected in the summary statistics, for example, the kurtosis of the LIFE score distribution increases from 16.6 to 18.4. This flattening of the hydroecological response is a possible indication of a reduction in biodiversity. If this were to be the case, this would increase the vulnerability of the river overall, monocultures being far more susceptible to local extinction. Further, the reduced frequency of events where LIFE scores fall very low, could impact negatively upon the river, robbing the ecosystem of vital, natural reset events (Everard, 1996; Lake, 2003).

4.5. Framework limitations

Limitations of the framework centre around the assumptions of stationarity and data availability. In climate change modelling, projections are often based on historic climate, with the assumption that the statistical properties of the climate remain stationary. This assumption is inherited under both hydroclimatic and coupled modelling. The corollary is an enforced assumption that ecological response remains the same as it is now; consequently, at this time, it is not possible to account for the adaptive response of the riverine community.

A barrier to hydroecological studies has been the lack of paired long-term hydrological and ecological time-series (Monk et al., 2007, 2012). This problem persisted in the development of the hydroecological model. For example, in the UK, routine macroinvertebrate sampling began circa 1990 (Murray-Bligh, 1992). Therefore, given the baseline of 1960–1990, validation is limited. To address this, an alternative baseline was derived. The use of climate projections with a more up-to-date baseline, for example, the soon to be released UKCP18 projections or a WG trained using CMIP5 or CMIP6 climate data would also address this.

5. Conclusions

The implications for flow regime make rivers among those ecosystems most sensitive to climate change (Death et al., 2015; Watts et al., 2015). Whilst studies have attempted to assess the impact of climate change on hydroecological response, methods are often qualitative or follow quantitative methods of limited scope. The resulting lack of clarity renders the fallout for ecosystem services effectively an unknown. In answer, the proposed framework provides a quantitative approach, developed using methods which minimise uncertainty (in line with recommendations in Clark et al., 2016).

The ability of the framework has been illustrated through application to a case study river. The projected hydroecological response in April–June, the period of peak MI activity in the river, is considered under the A1F1 high emissions scenario in the 2050s. The hydroecological response is in line with climate projections for the East Anglia region. The projections indicate that a reduction in biodiversity is *virtually certain*; a possible disruption to low flow processes essential to ecosystem functioning is less strongly indicated. It should be noted that, whilst the projected hydroecological change may be limited, the River Nar is strongly influenced by groundwater (BFI = 0.91). Consequently, the impact of changes in precipitation may be reduced; thus, greater change in response might be expected in catchments where surface runoff dominates.

In summary, the proposed framework serves as a new and dynamic tool with the potential to provide valuable information in the pursuit of more accurate assessments of the impact of climate change on river ecosystems. Critically, and possibly uniquely in the field (Bennett et al., 2013), the end user will also be provided with a quantifiable measure of uncertainty in the hydroecological projections. Further applications of the framework include water resources planning and future environmental flow management. In recent years, hydroecological modelling is often undertaken using a regime-based spatial framework (for example Monk et al., 2011; Zhang et al., 2012). In a similar manner, the proposed framework may be extended to cover multiple rivers of similar flow regime classification. Such generic projections of the impact of climate change on hydroecological response might thus be used to plan wider adaption measures, including for ungauged rivers, where appropriate. The projections may also be used to assess the implications of climate change on the provision of instream ecosystem services (e.g. through the framework set out in Ncube et al., 2018).

Data availability

Consent has not been given to share the data used in this study; however, these data are freely available from the original sources: the Environment Agency (EA, 2018; macroinvertebrate sampling records); Met Office (2016; climate, precipitation and temperature); National River Flow Archive (CEH, 2018; gauged flow at Marham); and data requests for the climate projections may be submitted using the UKCP09 web-based portal (http://ukclimateprojections-ui.metoffice.gov.uk/ui/admin/login.php).

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Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envsoft.2019.01.004.

Appendix A. Uncertainty

A.1 Stages 1 and 2

Table A1
Types and sources of uncertainty that are addressed in stages 1 and 2 (hydroecological and hydrological modelling) of the proposed framework.

Stage	Type of uncertainty	Source	Controls
1	Sampling and measurement error	Input data	Standardised methodology for the collection of macroinvertebrate samples. *Case study specific.*
			Quality control checks on observed flow data. *Case study specific.*
	Variability	Climate internal variability	Length of observed time-series; covering range of climatic periods (wet/dry). *Case study specific.*
	Structural uncertainty	Model selection	PCA: Addresses parameter redundancy.
			IT: Genetic algorithm searches for global optimum rather than local.
			Multi-model average, not a single best model.
	Parameter uncertainty	Model selection and parameterisation	Confidence intervals.
			Weight of supporting evidence, referred to as 'importance'.
2	Measurement error	Input data	Quality control checks on observed flow and climatic data.
			The modified covariance approach does not calibrate based on goodness of fit statistics, thereby reducing the bias of the parameterised model (see also ref myself).
	Variability	Climate internal variability	Length of observed time-series; covering range of climatic periods. *Case study specific.*
	Structural uncertainty	Model structure	The modified covariance approach rejects model structures if the observed and simulated moments do not coincide.
	Parameter uncertainty	Parameterisation	The modified covariance approach focusses on replicating the essential characteristics of the catchment explicitly.
			The relative importance of the HIs is known; error thresholds for each HI may be specified accordingly.
		Equifinality	The modified covariance approach considers the full parameter space which is narrowed down to a small region which is able to best replicate the HIs of interest.

A.2 Stage 3 – Climate projections

Climate change projections are central to the application of the proposed framework. It is recommended that probabilistic climate projections, which consider a range of impacts, be used when applying the proposed framework. In the case study application, the UKCP09 probabilistic climate change projections are used, specifically, the weather generator product. The application of the framework is not limited to UKCP09, other sources of probabilistic climate change projections include: the COMEPRO project in the Mediterranean region (Kaspar-Ott et al., 2016; Ring et al., 2018); the MIT IGSM-CAM framework (Monier et al., 2013a), applied over Northern Eurasia (Monier et al., 2013b); and UKCP18, the next iteration of UK Climate Projections, based on the Research Concentration Pathways from AR5 (Met Office, 2018a). Equally, projections may be produced via weather generator may be used directly; for example, the Vector-Autoregressive Weather Generator (Schlabing et al., 2014).

The UKCP09 identifies three major sources of uncertainties in their climate projections (Murphy et al., 2010): epistemic uncertainty (incomplete understanding of climate system processes), internal climate variability, and scenario uncertainty. A summary of the controls introduced in UKCP09 to minimise this uncertainty is detailed in Table A2.

Table A2
Sources of uncertainty in the UKCP09 weather generator climate projections and the controls in place to minimise this; based on Murphy et al. (2010).

Source	Controls
Epistemic uncertainty	A perturbed physics ensemble of the variance (Clark et al., 2016), e.g. different mathematical representation of the processes, interactions and feedbacks.
Variability	Multiple runs with the same initial conditions for each ensemble. Weather generator simulations based on statistical characteristics in the observed data. Simulations pick up more extreme climatic events (Schlabing et al., 2014).
Scenario uncertainty	There is a lack of agreement in how relative probability should be assigned to emissions scenario. To address this, UKCP09 presents three emissions scenarios: low, medium and high.

Appendix B. Information theory

B.1 Model evaluation

Although the overall concept of information theoretics may be unknown to the reader, certain aspects should be familiar. Based on "deep theoretical foundations" (Burnham and Anderson, 2001, p. 244), the concept and application are conspicuously simple. Candidate models are evaluated over three steps: 1) measuring the information lost in each approximating model; 2) determination of the evidence in support of each model; and 3) multi-model inference of a final model structure from the candidate set.

Step 1 *Loss of information from model f*

Kullback-Leibler (K-L) gives a measure of the amount of information that is lost when model g is used to approximate reality, f. A model which loses the least information, i.e. has the most supporting evidence out of the candidates, can be considered the best approximation of reality.

The information loss $I(f, g)$ is determined through computation of information criteria (IC). A multitude of IC exist, some of which with the reader is undoubtedly familiar. The Akaike Information Criterion (AIC) represents the standard estimate of Kullback-Leibler information (Burnham and Anderson, 2002). In hydroecological modelling, the sample size, n, is often small relative to the number of variables, K. A second order bias corrected version of AIC, AICc, can account for this through the addition of a second penalty (Burnham and Anderson, 2002):

$$AIC_c = AIC + \frac{2K(K+1)}{n-K-1} \tag{B1}$$

Step 2 *Evidence in support of model g_i*

The value of AIC is dependent on the scale of the data, the goal is to achieve the smallest loss of information given the data. This difference is rescaled and ranked relative to AIC_{min}:

$$\Delta_i = AIC_{ci} - AIC_{c\,\min} for\ i = 1,\ 2,\ \ldots,\ R. \tag{B2}$$

The value of Δ_i may be interpreted through a rule of thumb (based on likelihood intervals): $\Delta_i < 2$, there is substantial supporting evidence for model g_i; $4 \leq \Delta_i \leq 7$, the models are not as competitive; and if $\Delta_i > 10$ it can be assumed that there is strong evidence *against* model g_i (Burnham and Anderson, 2002). From this measure of evidence, the *likelihood* that model g_i is the best approximating model can be determined. This is known as the Akaike weight, w, ranging from 1 to 0, for the most and least likely models respectively:

$$w_i = \frac{exp\left(-\frac{1}{2}\Delta_i\right)}{\sum_{r=1}^{R} \exp\left(-\frac{1}{2}\Delta_r\right)} \tag{B3}$$

The use of the Akaike weight allows for clearer inference when considering the candidate models.

Step 3 *Multi-model inference*

When using information theory model selection, the best approximating model is inferred across the entire candidate set. This is achieved through consideration of a weighted combination of all candidates. Parameter averages, $\hat{\hat{\theta}}$, are simply the sum of the Akaike weights for each model that contains the predictor, $\hat{\theta}$:

$$\hat{\hat{\theta}} = \sum_{i=1}^{R} w_i \hat{\theta}_i \tag{B4}$$

As a result, the parameter averages are ranked, such that the highest value represents the most important in the model. This eliminates the problem of multiple equally plausible models with different parameter structures (equifinality).

B.2 Application using glmulti

The package *glmulti* streamlines the above steps into a single function (Calcagno, 2013). The fundamentals of the algorithm and approach are available in Calcagno and de Mazancourt (2010).

A subset of models was determined using the function glmulti. The function was applied five times to ensure convergence to a consensus of model subsets, with the function coef applied to determine the IT multi-model average. The number of indices is reduced by removing those indices where both coefficient and standard error are zero and to within the 95% confidence interval, by ordering by descending importance: ($importance_i$/ cumsum (importance)) < 0.95; this is illustrated in Table B1 overleaf.

Table B1
The structure of the hydroecological model prior to final removals (detailed above). Hydrological seasons are indicated by W (winter) and S (summer); the facets of the flow regime are denoted as M (magnitude) and R (rate of change). The removed indices occupy the final five rows, reasons indicated in bold.

#	Season	*Time-offset*	Index	Facet	Definition	Coefficient	Importance	Unconditional variance	Cumulative evidence weight
0	–	–	intercept	–	–	7.64	1	2.36	0
1	W	0	10R90Log	M	Log ratio 10th/90th percentile flows.	0.07	0.86	0	0.27
2	W	0	riseMn	R	Mean rise rate in flow.	0.07	0.07	0.05	0.95
3	S	0	Q80Q50	M	Q80 flows relative to median.	0.93	0.51	1.3	0.68
4	S	1	logQVar	M	Variance in log flows.	−0.5	0.37	0.57	0.8
5	S	1	Q90Q50	M	Q90 flows relative to median.	0.3	0.19	0.28	0.86
6	S	1	Q70Q50	M	Q70 flows relative to median.	0.11	0.09	0.05	0.93
7	S	1	RevPos	R	Number days when flow is increasing (positive reversals).	−0.04	0.8	0	0.52
–	W	0	25R75Log	M	Log ratio 25th/75th percentile flows.	**0**	0.12	**0**	0.9
–	W	0	20R80Log	M	Log ratio 20th/80th percentile flows.	**0**	0.05	**0**	**0.97**
–	W	2	MaxQ50	M	Maximum flow relative to median.	**0**	0.04	**0**	**0.98**
–	W	2	MaxMonthlyMed	M	Median maximum flow relative to median flow across all years.	**0**	0.03	**0**	**1**
–	S	0	Q90Q50	M	Q90 flows relative to median.	0.02	0.04	0.01	**0.99**

Appendix C. Case study

C.1 Hydroecological model – Index contribution

The contribution of each HI to hydroecological response was determined using the baseline data (1961–1990). Each of the 10,000 WG variants and hydrological year were considered independently. For each of these iterations, the relative contribution of the HI was determined:

$$\frac{\textit{index value} \cdot \textit{index coefficient}}{\sum \textit{index value} * \textit{index coefficient}} \tag{C1}$$

C.2 Hydroecological model – Validation with observed data

Data represents a key limiting factor to hydroecological modelling, with long-term (> 15–20 years) macroinvertebrate community data, at the species level, uncommon (Monk et al., 2012); Consequently, the length of the time-series in hydroecological modelling is insufficient for split-sampling (calibration and validation); this is commonplace in hydroecological modelling (Monk et al., 2012; Environment Agency, 2018).

The exploration of the model uncertainty serves as one approach to address the validation. Further validation is considered through comparison of simulated species LIFE scores (1991–2017) to three data sources summarised in Table C1; see Figure C1 for validation. The following should be considered when interpreting Figure C1:

- As discussed previously, LIFE score differences across taxonomic level are inevitable;
- Differences in LIFE scores of the same taxonomic level are due to known errors within the BIOSYS records; BIOSYS stat that corrections to address these inconsistencies are in progress (Environment Agency, 2018);
- April 1995–September 1997 saw extremely low rainfall, leading to errors in the recording of low flows (NRFA, 2014). This discrepancy may be the reason for the differences in observed and simulated values. It should be noted that the hydroecological model was not trained on data marked as suspect; this data is included in Figure C1 to allow for the fitting of trendlines.

Table C1
Data sources considered for the additional validation of the hydroecological model. *Years of data excluding training data (1993–2012).

Raw MI data provided	Taxonomic level	Source of LIFE score	Years
Yes	Species	This study	2013–2014*
Yes	Family	This study	1986–2014
No	Family	The Freshwater and Marine Biological Surveys England archive, known as BIOSYS (Environment Agency, 2018)	1991–2018

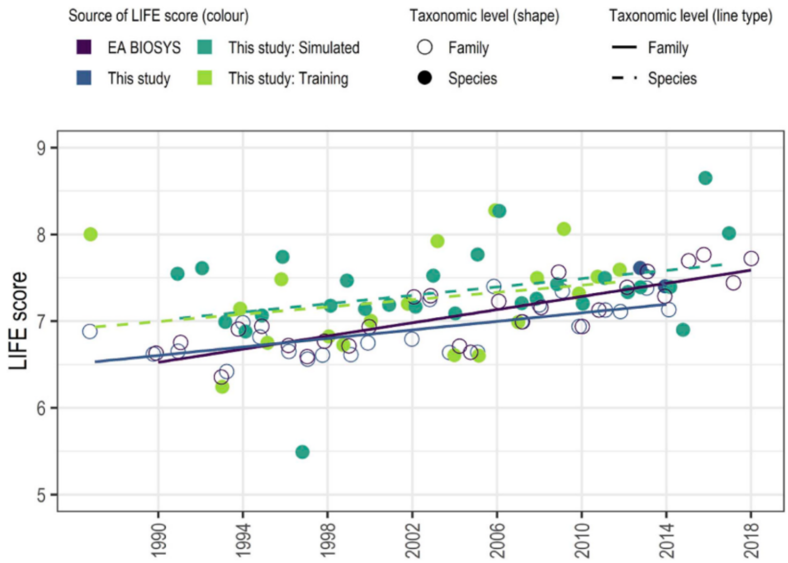

Fig. C1. Comparison of LIFE scores across data sources (see Table C1). Trend lines are fitted for each data source (with the exception of species LIFE, 2013–2014 insufficient data).

The two dashed lines represent the comparison of the training data (light green) and model simulations (dark green); the similarity in the slope of the lines indicates a high level of agreement in LIFE scores. Only two additional species LIFE scores are available (2013 and 2014; solid blue circles); it can be seen that these values are consistent with the observed training data trendline (light green dashed line).

Two sources of observed family LIFE scores are available; see above for notes on differences between the data sources.

The slope of the trendline for family LIFE scores, determined as part of this study (solid blue line), is similar to the observed training data; the underestimation of LIFE scores may be attributed to the difference in taxonomic level. For the EA BIOSYS data, a good level of agreement is again indicated; though it can be seen that the validity of the model improves over time.

C.3 Hydrological model – Validation with observed data

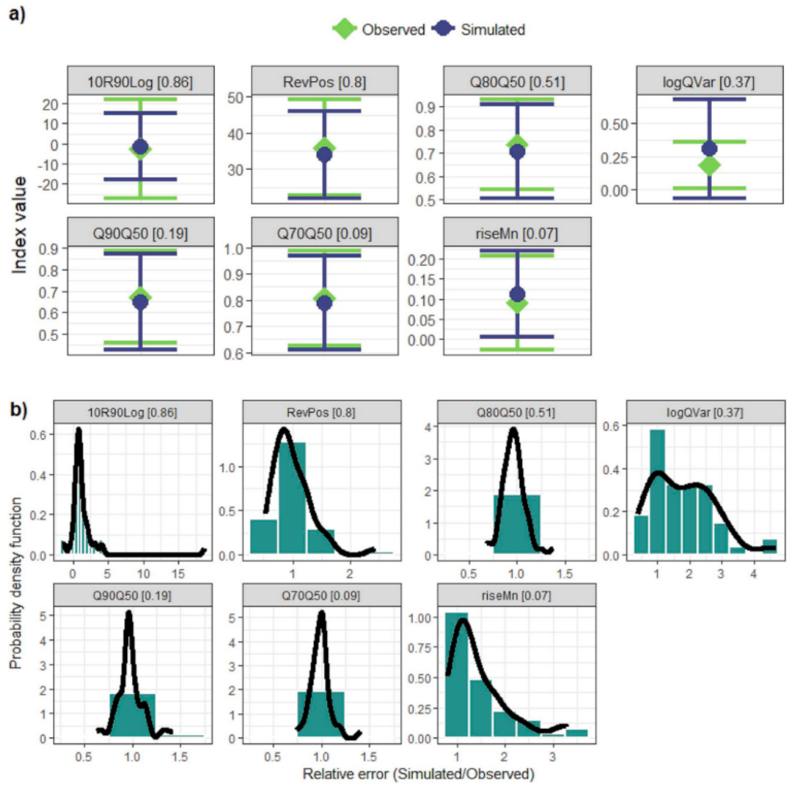

Fig. C2. Validation of the hydrological model using observed data. **(a)** Comparison of the mean and 95% confidence interval (2 standard deviations). **(b)** Probability density function of the relative error; a value of one indicates perfect agreement between model ~ observations.

C.4 Hydrological model – Validation with projections

Differences in the 95% CI for the index *10R90*Log are the result of a single outlier observation during the 30-year time period (note that the other two time periods are 4 and 7 years in length). It is also observed that the impact on hydroecological response reduces as *10R90*Log increases to more extreme values (± 10 specifically).

Table C2
Validation of the framework using the UKCP09 projections on the baseline.

Index	Time period	Lower quantile	Median	Upper quantile	− 95% CI	+ 95% CI
10R90Log	1961–1990	−1.39	0.15	2.17	−96.58	96.88
10R90Log	1986–1990	−1.35	0.01	0.81	−27.83	27.86
10R90Log	2010–2017	−0.17	0.05	0.43	−19.47	19.58
RevPos	1961–1990	0.86	1	1.2	0.28	1.72
RevPos	1986–1990	0.82	0.9	1	0.65	1.15
RevPos	2010–2017	0.85	0.95	1.07	0.59	1.32
Q80Q50	1961–1990	0.9	1.01	1.13	0.65	1.37
Q80Q50	1986–1990	0.9	0.99	1.06	0.76	1.22
Q80Q50	2010–2017	0.98	1.05	1.13	0.78	1.32
logQVar	1961–1990	0.57	0.95	1.59	−1.28	3.17
logQVar	1986–1990	0.55	0.92	1.49	−0.75	2.58
logQVar	2010–2017	0.34	0.58	1.06	−1.24	2.41
Q90Q50	1961–1990	0.87	1.02	1.19	0.56	1.48
Q90Q50	1986–1990	0.86	0.98	1.08	0.67	1.28
Q90Q50	2010–2017	0.92	1.02	1.09	0.71	1.33
Q70Q50	1961–1990	0.92	1.01	1.1	0.71	1.3
Q70Q50	1986–1990	0.92	0.98	1.04	0.8	1.16
Q70Q50	2010–2017	0.96	1.02	1.13	0.76	1.28
riseMn	1961–1990	0.65	1.08	1.89	−1.36	3.53
riseMn	1986–1990	0.56	0.93	1.36	−0.38	2.24
riseMn	2010–2017	0.87	1.43	2.45	−1.79	4.66

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4. AFTERWORD

This publication in *Environmental Modelling & Software* introduces the coupled modelling framework as a complete whole (objective 3.2). Extensive appendices serve to provide further depth of detail on the more esoteric subjects so as not to disrupt the coherent story of the framework. A review of the literature has previously shown that the use of the component models is well-established, with the earlier chapters also establishing the validity of the author's newly developed approaches. In the publication, the successful application to the principal case study establishes the validity of the coupled modelling framework (objective 3.3) and provides the answer to the third research question – climate change projections may be used to determine quantitative hydroecological outcomes.

For the case study application, the publication discusses impacts in order to demonstrate the facility of the framework and the apt method of interpreting its results. A limited hydroecological response, relative to the baseline, was projected under the A1FI high emissions scenario in the 2050s (2031-2060). To establish the validity of the results, and a depth of understanding, projections of hydroecological response were considered with respect to:

- The relative contributions of the hydrological indices to the Lotic-invertebrate Index for Flow Evaluation (LIFE) score (i.e. identified through sensitivity analysis). The impact of the changed climate is, in part, minimised due to offsetting effects in the hydrological indicators;
- Schlabing *et al*. (2014), where the projected response was also limited under the mean change signal;
- Climate projections and the dominant hydrological processes in the East Anglia region suggest a more limited hydrological response to climate change;
- A look to the Environment Agency's *Freshwater and Marine Biological Survey for Invertebrates England* (BIOSYS), a database of ecological data for 548 English catchments, revealed a limited range in variation in LIFE under the present climate.

Whilst at first glance these results, indicating a limited response, seem positive for the case study river, the publication does project a concurrent fall in variability. This fall in variability suggest a reduction in biodiversity raising real concerns over the resilience of the river ecosystem. The potential for reduced ecosystem functionality in the relatively nearfuture serves to highlight the importance of research which looks to understand hydroecological response to climate change.

The projections of limited change also serve to highlight the main limitation of the coupled modelling framework – the assumption of stationarity – that the underlying hydrological processes and hydroecological relationships will remain the same in the future.

The sensitivity analysis of the hydroecological relationship highlights that even a minor reordering of indicator importance – for example, the least important index becomes the more important – could significantly alter the impact of climate change on hydroecological response. However, it should be noted that, at present, the assumption of stationarity underpins the majority of climate change impact studies, including water resources planning & management (Bayazit, 2015). Any allowance for potential non-stationarity would require recourse to hydrological modelling – an area which remains in its infancy right now (Bayazit, 2015; Beven, 2016).

The application of the coupled modelling framework to a single case study represents an additional limitation; it is thus not possible to directly confirm the wider applicability of the framework beyond the principal case study. The additional computational load rendered application to the four further case studies, considered in chapters 3 and 4, beyond the scope of this study. The consideration of the results in context, as outlined above, can be considered to go some way to redress this. This constraint should not detract from the promising advancements achieved through the development of the framework.

5. CONCLUDING REMARKS

Rivers have been identified among the ecosystems most sensitive to climate change. Attempts to assess the impact of climate change on hydroecological response have, largely, been qualitative, or of limited scope. This thesis aims to address this through the development of a coupled modelling framework. Chapters 3 and 4 focussed on establishing methods for the development of the component models, whilst this chapter and final publication served to complete the framework (objective 3.2).

The characterisation and minimisation of uncertainty has been central to the development of the framework. Accordingly, this chapter begins with a consideration of uncertainty at each stage across the coupled modelling framework. This serves to both satisfy objective 3.1 and provide a clear summary to the reader.

The ability of the framework was illustrated through application to the principal case study. The results highlighted both the need for frameworks such as this, as well as the limitations associated with the assumption of stationarity. The publication also provides a review of applications and limitations; a more comprehensive review follows in *Chapter 6 – Discussion.*

CHAPTER 6. DISCUSSION

The aim of this thesis is to develop a coupled modelling framework to assess the (riverine) hydroecological impact of climate change. The framework development was structured around three research questions, which were addressed through four academic journal publications. A brief overview follows.

Research question 1 – Can hydroecological models account for a potential delay in hydroecological response?

The first research question looked to establish whether delays in macroinvertebrate response to perturbation could be accounted for in hydroecological modelling. A proof of concept was established through the first publication (Visser *et al.*, 2017). Looking to improve the robustness of the approach, the methodology was further refined in the second publication using information theory (Visser *et al.*, 2018). Five case studies were used to establish the validity of the method. The derived methodology forms stage 1 of the coupled modelling framework (Figure 1-4). See *Chapter 3 – Hydroecological modelling* for details.

Research question 2 – Can hydrological modelling be optimised towards the preservation of ecologically relevant characteristics of the flow regime?

There are significant limitations and uncertainties associated with the use of hydrological models for the replication of ecologically relevant hydrological indicators. Research question 2 asks how these limitations may be overcome. This was addressed through identification of the key challenges faced and subsequent modification of Vogel and Sankarasubramanian's (2003) covariance approach. Detailed in the third publication (Visser-Quinn *et al.*, 2019b), the modified covariance approach was validated through application to five hydrologically diverse case study catchments. Derivation of the hydrological model, through the modified covariance approach, forms stage 2 of the coupled modelling framework (Figure 1-4). See *Chapter 4 – Hydrological modelling* for details.

Research question 3 – Can climate change projections be used in the determination of quantitative hydroecological outcomes?

The final research question looks to bring the findings from questions 1 and 2 together to form the coupled modelling framework. In order to answer this question, it was first necessary to consider the framework in the context of uncertainty, the characterisation and minimisation of which has been central throughout. This was followed by the fourth publication (Visser *et al.*, 2019b), which detailed the coupling of the two component models, as well as validation through application to the principal case study. See *Chapter 5 – Coupled modelling framework* for details.

This chapter is organised firstly by research question, providing: (1) an overview of the outcomes; (2) consideration of the relevance of the work in the context of the framework, the field & beyond; (3) the applicability of the work. In discussing research question 3, the kind of insights which might be gained through application of the coupled modelling framework are also considered. The subsequent section considers the limitations of the work contained herein. This is then followed by a review of scope for further research, informed by the current trajectory of the research in the field(s).

1. RQ1 – CAN HYDROECOLOGICAL MODELS ACCOUNT FOR A POTENTIAL DELAY IN HYDROECOLOGICAL RESPONSE?

1.1 OVERVIEW

The substantial refinement of current hydroecological modelling practice is central to the coupled modelling framework; the derived methodology represents stage 1 (Figure 1-4).

Methods for the quantification of the hydroecological relationship are well-established. Numerical models are used to capture the link between biological indicators, the proxy for river health, and a suite of hydrological indicators, known to be ecologically relevant. The structure of model is predominantly determined through stepwise methods.

Previous work by the author (Visser, 2014), coupled with a review of hydroecological studies over the past 20-years, indicated that there may be a delay in ecological response to flow disturbances; this phenomenon was predominantly observed in rivers with a significant groundwater contribution. Due to a focus on immediately preceding flows (within 6 months), current hydroecological modelling approaches are simply unable to account for this phenomenon.

Being thus informed, research question 1 asked whether this potential delay in hydroecological response may be accounted for; the research question was guided by three research objectives. The first step was to establish a proof of concept (objective 1.1). In light of previous observations of lag by the author (Visser, 2014), the River Nar was selected as the principal case study. The aim was to establish whether this potential source of epistemic uncertainty – a process which is unknown and/or not accounted for by the model – can be accounted for through current modelling practices (as described above). The presence of this potential lag was systematically explored in the first publication, *Macro-invertebrate Community Response to Multi-annual Hydrological Indicators* (Visser *et al.*, 2017), where this putative phenomenon was represented by a reduced suite of time-offset hydrological indicators. The results strongly suggested the existence of lag in hydroecological response (for the principal case study, a groundwater-fed chalk river). The wider applicability was tested under objective 1.3.

Quantification and minimisation of uncertainty is central to the wider coupled modelling framework. Whilst the inclusion of time-offset indicators may serve to reduce the epistemic uncertainty, the additional complexity may, in turn, lead to the addition of other sources of uncertainty. Thus, the focus of objective 1.2 was to improve the statistical robustness of the modelling approach.

Presently, hydroecological datasets are limited in length; whilst this will inevitably improve over time, it is, presently, essential to maximise parsimony (Burnham and Anderson, 2002; Bolker, 2009). Position arguments in Whittingham *et al.* (2006) and Burnham *et al.* (2011), among others, frequently cite information theory as the alternative to stepwise methods. This theory allows for the determination of a multi-model average, through which both structural and parameter uncertainty may be accounted for.

Whilst stepwise selection and information theory have been compared in other fields, it was unclear how such observations might transfer into hydroecological modelling. This was subsequently clarified through the second publication, *Complexity in hydroecological modelling: A comparison of stepwise selection and in-formation theory* (Visser *et al.*, 2018). As with the first, the focus remained on the principal case study. The limitations of the stepwise approach were considered through application of both approaches, with and without the addition of time-offset hydrological indicators (representing the lag in response), alongside evidence garnered from the available literature.

Critically, the work highlighted predictions from an information theory multi-model average as more realistic than those models derived following a stepwise approach. The importance of accounting for the sources of uncertainty (parameter and model structure) was thus established. Of comparable value, is the measure of importance made available by information theory: the weight of evidence in support of the inclusion of the model parameters, the ecologically relevant hydrological indicators. Looking to the principal case study, two of the ecologically relevant hydrological indicators represent the winter season. With the measure of importance, it is also possible to state that the magnitude indicator, *10R90Log*, dominates the winter processes, whilst the rate of change indicator, *riseMn*, exerts only minimal control.

Objectives 1.1 and 1.2 provided a proof of concept for both the inclusion of time-offset hydrological indicators, and the use of the information theory approach. Having been only applied on a single case study, and a limited suite of hydrological indicators, objective 1.3 saw the consideration of: (1) the full variability of the flow regime; and (2) the wider applicability of the approach, beyond a single groundwater-fed river. To this end, the refined methodological framework was applied to the principal, and four additional, case studies. Just under half of indicators were time-offset, confirming the importance of delayed response to the hydroecological relationship. An indication of the validity of the refined approach, model error and uncertainty were shown to be in the same order of magnitude as publication 2. However, due to data limitations, it was only possible to assess parameter uncertainty for three of the five catchments.

In satisfying these three objectives it is possible to answer research question 1 – *Can hydroecological models account for a potential delay in hydroecological response?* The successful application of the refined methodology illustrates that this is indeed possible. Additionally, this work suggests that cumulative antecedent flows have an important role irrespective of flow regime. Boulton (2003, p. 1181) argues that not accounting for lag *"may only reveal part of the impact and miss longer term and perhaps more profound differences"*: almost a generation later, the work presented here supports that claim.

1.2 RELEVANCE

Pressure on river systems, the result of human interference, acts as either cause or amplifier of flow-generated disturbances (Acreman, 2001), with grave implications for both resistance and resilience. Increasing understanding of the hydroecological relationship is key to enhancing future resilience (Arthington, 2012b). In pursuit of this, the 2018 Brisbane Declaration specifically calls to the research community to look beyond *"established approaches to the science and management of water for the environment"* (Arthington *et al*., 2018, p. 3). Such improvements in predictive capacity are considered central to increasing the practical application of environmental flow methods, which has to date, been extremely limited (Arthington *et al*., 2018; Poff, 2018).

In answer to the above, the work undertaken as part of research question 1 makes a contribution to improving the current understanding of hydroecological relationships, with important implications both for the field of hydroecological modelling more generally, as well as in the context of the coupled modelling framework. Delays in hydroecological response are in evidence across a range of flow regimes. This may prove more important in the future under a changing climate: where shifts in the frequency and magnitude of flow-generated disturbances are projected (Cisneros *et al.*, 2014; Watts *et al.*, 2015). The presence of lag, coupled with more frequent disturbances, reduces the time for recovery, and may thus lead to losses in resiliency, which may be further amplified by increases in human demand for water (Arthington, 2012b). In a world where informed water management decision-making is the objective, accounting for this phenomenon appears vital, perhaps offering an opportunity for better decision-making, mitigation, and adaption strategies.

As well as being central to the framework development, the move towards the characterisation and minimisation of uncertainty also represents an important shift in focus within the field of hydroecological modelling. This may contribute towards a much-needed increase in confidence when it comes to real-world application. What has been established is a solid framework, upon which it may be hoped that a more informative and robust hydroecological modelling approach may be built.

An unexpected outcome from publication 2 was the failure of the stepwise model (with lag) to incorporate the winter recharge of the aquifer; a process essential to a groundwater-fed chalk river such as the River Nar (Sear *et al.*, 2005). This failure to represent a true picture of reality suggests the stepwise approach may inherently contribute to epistemic uncertainty. This further serves to highlight the likely unsuitability of the current stepwise approach in hydroecological modelling.

2. RQ2 – CAN HYDROLOGICAL MODELLING BE OPTIMISED TOWARDS THE PRESERVATION OF ECOLOGICALLY RELEVANT CHARACTERISTICS OF THE FLOW REGIME?

2.1 OVERVIEW

Despite a known lack of skill in preserving ecologically relevant characteristics of the flow regime (Murphy *et al.*, 2012; Shrestha *et al.*, 2014, 2016; Vis *et al.*, 2015; Pool *et al.*, 2017; Mackay *et al.*, 2019; Worthington *et al.*, 2019), hydrological models are central to assessing the impact of hydrological alteration (Poff *et al.*, 2010) and hence the development of the coupled modelling framework. In view of this, the second research question centred on hydrological model optimisation, with the refined methodology forming stage 2 of the coupled modelling framework (Figure 1-4).

To guide the model optimisation, a summary of the key challenges inherent to the preservation of these characteristics was first established (objective 2.1). These can be summarised as the use of unsuitable objective functions and metrics in:

(1) Model parameterisation, and;
(2) Model evaluation.

At the same time, the following are typically neglected:

(3) Identification of hydrological indicators which are relevant to the catchment;
(4) Minimisation and characterisation of uncertainty, and;
(5) Validation of model structure.

The second objective looked to address these challenges through the third publication (Visser-Quinn *et al.*, 2019b), *Replication of ecologically relevant hydrological indicators following a modified covariance approach to hydrological model parameterization*. The author looked to Vogel and Sankarasubramanian's (2003) covariance approach, where the focus is on replicating a specific hydrological signature based on the covariance structure of the observed input / output. The region of parameter space which is best able to replicate the characteristics of the hydrological indicator is subsequently identified. The approach was modified to broaden the scope from a single-indicator problem to a multiple-indicator problem. Informed by hydroecological modelling outcomes, this is achieved through the determination of the limits of acceptability (error thresholds) based on the importance of each ecologically relevant hydrological indicator (ER HI). The corresponding plausible parameter space is thus identified ($n \cong 20$).

In the course of the third publication, the modified covariance approach was validated (objective 2.3) through application to five hydrologically diverse catchments. The hydroecological models determined in the course of objective 1.3 were used to identify the ecologically relevant hydrological indicators. The invalidation of certain model structures highlighted one of the main benefits of the modified covariance approach. It was in the replication of specific indicators or facets of the flow regime, across all the case studies, that differences in performance and consistency were observed (as opposed to between catchments). For example, timing facets of the flow regime were best replicated, whilst rate of change indicators were poorest. The length of the available time-series had no discernible impact.

Relative to previous studies (Shrestha *et al.*, 2014, 2016; Vis *et al.*, 2015; Pool *et al.*, 2017), this application considered a broader range of ecologically relevant hydrological indicators, representing all five facets of the flow regime (Table 1-1), whilst also offering improvements in performance and consistency. This work, then, provides a strong indication that hydroecological modelling can indeed be optimised for the preservation of ecologically relevant characteristics of the flow regime.

2.2 RELEVANCE – REVIEW OF KEY CHALLENGES

The relevance of the modified covariance approach is assessed with respect to its ability to address the key challenges identified under objective 2.1 (summarised above). Section *2.2.1 Novelty* highlights how the approach identifies, and incorporates, catchment-specific ER HIs (challenge 3). Three of the five remaining challenges (one, four and five) relate to uncertainty in hydrological modelling; this is the focus of section *2.2.2 Characterisation and minimisation of uncertainty*. Blöschl and Montanari (2010) emphasise the importance of modelling approaches tuned towards minimising uncertainty, describing the use of hydrological models which attempt to model everything (i.e. the time series), as *"analogous to throwing the dice".* To close, section 2.2.3 considers challenge two, the (un)suitability of evaluation metrics.

2.2.1 Novelty

The novelty of the modified covariance approach lies in its ability to incorporate hydroecological modelling outcomes through a measure of statistical importance. As such, it is ideal as a means by which the research question may be answered. A total of forty distinct ER HIs were considered, representing all five facets of the flow regime (Table 1-1). It was thus possible to establish the relevance of the approach in a way which has not been possible in previous work (Shrestha *et al.*, 2014, 2016; Vis *et al.*, 2015; Pool *et al.*, 2017) which did not consider catchment-specific ER HIs. Overall model performance was shown to be comparable with these previous studies, the observed difficulties in replicating rate of change indicators in particular. The increased consistency with which the large suite of ER HIs was able to be replicated illustrates the relative success of the modified covariance approach.

2.2.2 Characterisation and minimisation of uncertainty

A focus of the covariance approach is the validation of the model structure prior to parameterisation (Vogel and Sankarasubramanian, 2003); this characteristic is retained in the modification presented in this thesis. The user is thus able to evaluate the ability of the model structure to capture the catchment hydrological processes. Models which are shown to be incapable of replicating these processes are rejected, ensuring that the model parameterisation achieves the right answers for the right reasons (Kirchner, 2006; Gupta *et al.*, 2014). That is, epistemic uncertainty is minimised.

In the modified covariance approach, the limits of acceptability allow for the identification of a plausible parameter space. In identifying this region, model equifinality – the presence of multiple parameter sets capable of representing the desired hydrological outcome – is accounted for. Visualisation of the parameter space is central to the approach and may also serve to highlight the need to account for equifinality.

Hydrologic data may contain a large number of errors (Gupta *et al.*, 2014). Methods which do not focus on the replication of the time series directly, such as the modified covariance approach, are known to significantly limit the influence of input uncertainty (Westerberg *et al.*, 2011; Euser *et al.*, 2013; Gupta *et al.*, 2014); leading to greater overall confidence in the resulting models. In hydrological modelling more generally, there is, increasingly, a call to move away from replicating a hydrograph and move towards model fidelity through the replication of hydrologic signatures (Kirchner, 2006; Gupta *et al.*, 2014). The focus of the modified covariance approach on the minimisation and characterisation of uncertainty makes it ideal for these more general hydrological applications, including the replication of water resource management indicators and the development of regional hydrological models. For such applications, the need for a numerical measure of indicator importance may be addressed through the application of information theory in the same manner as described in chapter 3.

2.2.3 Suitability of evaluation metrics

Although not strictly a part of the modified covariance approach, the third publication also considers evaluation metric suitability (challenge two). The comparative studies make use of metrics which exhibit known bias. These same metrics were considered in this work, for the purposes of comparison, and to highlight their limitations. Alternative (less biased) metrics were applied to better evaluate model performance. In adopting this approach, the unsuitability of the Nash Sutcliffe Efficiency (NSE) (in the context of replicating ER HIs) was demonstrated. This exercise was undertaken in order to demonstrate, and evidence, the availability of more statistically robust alternatives.

2.3 WIDER APPLICABILITY OF THE MODIFIED COVARIANCE APPROACH

The explicit consideration of the outcomes of hydroecological modelling is perhaps both the most significant advantage, and disadvantage, of the modified covariance approach. Where sufficient ecological data is not available, it is not possible to account for indicator importance. Nonetheless, Pool *et al.* (2017) stresses that research should be moving in this direction. In future this may, then, represent an obstacle for all hydrological models looking to replicate ER HIs. In answer, work, such as this, may serve to improve the alignment of hydrological and ecological data collection.

The ways in which the modified covariance approach minimises hydrological model uncertainty may make it an attractive alternative to the traditional modelling approach, even in cases where the statistical indicator importance cannot be determined. In these instances, indicators may be assigned equal importance or values determined by the user; this is not dissimilar to current use of objective functions. This would also be applicable for more general hydrological applications where statistical models cannot be determined.

With regards to further work, further evaluation, through comparative assessments, would serve to highlight the capabilities, and limitations, of the modified covariance approach. Areas of particular interest are the comparison of hydrological models from different families (beyond the GR suite of models) and direct comparison with the traditional approach. Comparison with a traditional approach, informed by hydroecological modelling outcomes, would be of particular interest.

3. RQ3 – CAN CLIMATE CHANGE PROJECTIONS BE USED IN THE DETERMINATION OF QUANTITATIVE HYDROECOLOGICAL OUTCOMES?

3.1 OVERVIEW

Riverine hydroecological response to climate change has been limitedly considered. A summary of where research efforts have been focussed was provided with Figure 1 in the fourth publication (Visser *et al.*, 2019b, p. 13). The primary avenue of investigation, to date, has been the impact of temperature on ecology. These efforts were shown to have been predominantly qualitative in nature. The impact that the changed flow regime (as a result of climate change) would have on ecological response is little understood. Research question 3 asks whether it is possible to determine a quantitative measure of these hydroecological outcomes. The research question is the product of the previous two research questions and represents the main output of this thesis.

In the final stage of the framework, the two component models are coupled, with climate change projections serving as the model input. These projections represent a large portion of the uncertainty in the modelling chain. To ensure that the framework is clear and transparent about its treatment of uncertainty, the first objective under research question 3 required a summarisation of the uncertainty. The sources and efforts to minimise uncertainty across all stages were presented, alongside recommendations for potential user-input and therefore informed decision-making.

In order to fully answer the research question, validation and demonstration of the framework was necessary. This was achieved through the principal case study, the River Nar, a chalk stream in Norfolk, England. The coupled model was forced with projections from the UK Climate Projections 2009 (UKCP09) weather generator (SRES A1FI; 2050s time slice). Prior to validation of the framework in its entirety, the projections were validated, followed by the hydrological model. This then, indicated the completion of framework development.

3.2 RELEVANCE

This thesis opened with a conceptual framework, showing the links between environmental change, ecosystem functionality, and the delivery of the vital ecosystem services upon which humans depend (Figure 1-1). The biodiversity-stability hypothesis (Chapin *et al.*, 2000) states that biodiversity introduces redundancy in the system, thereby improving resistance and resilience. It was further established that: (1) climate is the main determinant of hydrological processes; and (2) it is through water, particularly rivers, that much of the impact of climate change will be felt. The majority of the world's rivers are degraded and under stress, growing water demand will only exacerbate this (Vörösmarty *et al.*, 2010; Arthington, 2012b). Nevertheless, the main challenge facing rivers, and hence river management, is climate change (Arthington, 2012b). It is for these reasons that the recently revised Brisbane Declaration (Arthington *et al.*, 2018) puts climate change adaptation at the heart of the new era of environmental flows science.

An understanding of how the riverine ecology might respond to this hydrologic alteration under a changed climate is necessary in order to determine appropriate mitigation and adaptation strategies. To date, the supportive research has been primarily qualitative in nature. In answer, this thesis has seen the development of a coupled modelling framework through which such quantitative hydroecological projections may be determined. Research questions 1 and 2 addressed concerns relating to the component models, whilst the final research question saw the output of the framework itself. In order to increase the credibility of these projections, the framework focuses on characterising, reducing, and quantifying the associated uncertainty.

3.3 APPLICATION

In developing this framework, this thesis establishes that it is possible to determine projections of hydroecological response to climate change. As stated in the second publication (Visser *et al*., 2018), hydroecological models may be derived at multiple scales: site, river or flow regime classification. Data availability per site may be significantly less than for the river in its entirety, thus the consideration of lag in ecological response is not practicable at such a fine spatial scale.

Application to individual rivers, as in the fourth publication, represents one of the potential applications of the framework. However, data availability and the required workload may be viewed as prohibitive for such applications; the impact of these obstacles to implementation is further considered under *4. Limitations*. Hydroecological and hydrological models are frequently developed at the regional level. Monk *et al*. (2008) have also shown that the length of the available times series for multi-river hydroecological studies may be extended through grouping of rivers by flow regime type; such applications are also possible in hydrological modelling; for example Bárdossy (2007) use flow regime type to model ungauged catchments. Extending the application of the framework in this way may be more practicable. The projections might thus be used to plan wider adaption measures, including for ungauged rivers, where appropriate.

3.4 POTENTIAL INSIGHTS

Whilst the focus of this thesis has been on the development of the framework, additional work was carried out to explore the impacts of climate change for the principal case study (beyond the application in the fourth publication); this work has been published in the journal *Water* and is available in *Appendix B*. The outcomes of this work are briefly considered here in order to highlight the kind of insights application that the framework may provide.

As in the fourth publication (*Chapter 5. Coupled modelling framework*) (Visser *et al.*, 2019b), minimal change in the mean hydroecological response was observed. This appears to be the result of the interaction among the hydrological indicators. Flows in the immediately preceding winter dominate hydroecological response, to the extent that they appear capable of wholly offsetting the impact of previous seasons. This highlights a previously unknown degree of flexibility in how the water in the catchment may be utilised.

In this supplementary publication, an increase in the probability and magnitude of extreme events, coincided with a reduction in internal variability. These impacts were manifest as early as the 2030s (2021-2050), raising real concerns over the resilience of the river ecosystem as a whole Such quantitative evidence, suggests an urgent case for further work of this type. Notably, this publication represents the first instance of quantitative projections of hydroecological response over time (2021 to the end-of-century, across three 30-year time slices).

The determination of the hydroecological projections enabled a qualitative assessment of the potential impact of climate change on ecosystem functionality. A functional matrix was developed, relating species-level macroinvertebrate functional flow preferences to functional food groups. The matrix indicates that almost none of the taxa observed in the River Nar would be able to perform their functional roles under the projected climate change. This could, in turn, lead to a reduced provision of ecosystem services and impair the resilience of the riverine system.

4. LIMITATIONS

4.1 OBSTACLES TO IMPLEMENTATION

4.1.1 Inertia – Resistance to change

Publication 2 (Visser *et al*., 2018, p. 4), states that the consideration of R-squared (or adjusted R-squared) and p-values, in combination with information theory is counter to the underlying philosophy of the latter; this is then subject to discussion at length (within the publication). The focus of information theory lies squarely upon the quantification of uncertainty, and importance, the relative weight of evidence in support of (the inclusion of) each model parameter. This is further alluded to in publication 4 (Visser *et al*., 2019). Despite this, one peer-reviewer of the submission remained insistent that these statistics be provided. Such adherence to the status-quo may explain the slowness of hydroecological modellers to adopt information theory. The author is currently at a loss as to how such a philosophical barrier may be overcome without a sea-change in wider attitudes.

Peer-reviewers, again, had some struggles with terminology, relevant to the field; in particular, what is meant by model calibration and validation; see *Glossary of terms* on page xi for further details. Reviewers also requested the NSE, despite the explicit evidence of its inappropriacy. Perhaps further work may help to promote the wider knowledge and understanding required.

4.1.2 Ecological data availability

Monk *et al.* (2006, 2012) highlight that hydroecological modelling is limited by the availability of ecological data. To demonstrate, the incorporation of a time-offset of just 2-years given a typical (according to Monk *et al.*, 2006) 20-year time series could lead to the loss of up to 5% of the available data. Going some way to assuage this concern, the case study applications in *Chapter 3 – 7. Validation* indicated a low relative error, irrespective of the length of the available time series. This appears to be, at least in some part, due to the implementation of the information theory approach.

The incorporation of a time-offset saw a two- or three-fold increase in the number of ecologically relevant hydrological indicators. The application of Principal Component Analysis (PCA) reduces this number considerably (to approximately 20), effectively negating the impact of this increase. However, Monk *et al*. (2007) have raised questions over the ability of PCA to identify the most relevant indicators. This was limitedly considered in the first publication (Visser *et al.*, 2017), with similar conclusions drawn. A review of hydroecological studies covering the past 20 years, revealed no similar observations, and thus this was not pursued any further in this body of work. However, this may represent an area with scope for further research, perhaps requiring some direct investigation into the underlying mathematics.

4.1.3 Climate projections and the need for a weather generator

Flow-generated disturbances are known to exert a strong ecological response (Lake, 2013). Thus, a comprehensive assessment of climatic variability and lower-probability events is key. In *Chapter 5. Coupled modelling framework*, the use of a weather generator is recommended due to their ability to produce multiple realisations, allowing for better representation of extremes.

The example application considered in the fourth publication (Visser *et al.*, 2019) made use of the UKCP09 Weather Generator. It should be noted that this is not applicable for further applications for the following reasons:

- The Special Report on Emissions Scenario projections are outdated, having been superseded by Representative Concentration Pathways (RCPs). Accordingly, UKCP09 was replaced by UKCP18 in 2018;
- As of 31 December 2018, the UKCP09 service has closed. The interface through which the weather generator was run is no longer available, though archived runs may be available through the Centre for Environmental Data Analysis catalogue;
- The projections were for the UK and only at a localised scale (single site).

As interest in climatic variability and extreme events grows, the number of stochastic weather generator options available is, however, only increasing. Potential options include: the vector-autoregressive weather generator (Schlabing *et al*., 2014); and the Advanced WEather GENerator (AWE-GEN) (Ivanov *et al.*, 2007; Fatichi *et al.*, 2011) developed at ETH Zurich which has been extensively applied for both hydrological and ecological purposes. A number of weather generators are also made accessible through packages in R, for example, Cordano and Eccel (2016). Whilst it is clear that the user may develop their own weather generator, the additional work required, coupled with the additional uncertainty, may represent significant limiting factors, potentially impacting upon the applicability of the framework to individual river systems.

4.2 NON-STATIONARITY

The hydroecological and hydrological models developed in this study, and in their respective fields more generally, make use of observed data, with a central assumption of stationarity. This assumption, in a hydrological context is defined by Klemeš (1989, p. 45):

> *"[stationarity] implies an assumption of a physical constancy of the mechanisms participating in the formation of the streamflow, from the regimes of precipitation and evaporation in the river basin, to geomorphological, pedological, and other physical conditions."*

Whilst it is well known that this assumption is not true (Klemeš, 1974, 1989), Razavi *et al.* (2015) highlight that the limited length of the observational records limits the ability to explore non-stationarity. Thus, models are necessarily developed upon an uncertain basis which may not be possible to quantify.

Non-stationarity represents an additional problem for climate change applications. The modeller assumes that the underlying relationships and processes hold true in the future – that they will not change. It is this highly dubious aspect of non-stationarity which represents a major limitation of current climate change impact studies. Areas where this non-stationarity may influence the coupled modelling framework are summarised below.

- The adaptive capacity of species is not well understood, thus the hydroecological relationship which underpins the framework may be subject to change. Indicators based on functional groups may serve to provide some (limited) additional information;
- This work has highlighted the difficulties in capturing observed hydrological processes, therefore, it could be said that modelling changes in these processes is beyond the present ability within the field;
- Stochastic weather generators are probabilistic models that reproduce climate based on the statistical properties of the observed time series (Themeßl *et al.*, 2011). This assumes that the dependency structure of the climate variables remains the same under a change climate;
- The assumption of stationarity in this work extends to the socio-economic climate and land use. This is, likely, the most unrealistic premise and may potentially be addressed through cross-sectoral modelling. This is further discussed as part of *5. Scope for further research.*

The above uncertainties may be further compounded as the projections are forced through the modelling chain: a limitation of the majority of climate change impact studies (Burkett *et al.*, 2014; Harrison *et al.*, 2016; Rosenzweig *et al.*, 2017; Sušnik *et al.*, 2018).

5. SCOPE FOR FURTHER RESEARCH

The work contained in this thesis represents an early step in pursuit of the Brisbane 2018 Global Action Agenda (research goals). There exists significant scope for further developments. Discussed herein are three options for future work in sympathy with the direction of travel in the field of environmental flows and beyond.

5.1 DROUGHT-FOCUSSED BIOTIC INDEX

A natural sequitur to this work would be to consider the recently developed drought-focussed biotic index, *Drought Effect of Habitat Loss on Invertebrates* (DELHI) (Chadd *et al.*, 2017). Similar to the Lotic-invertebrate Index for Flow Evaluation (LIFE), the DELHI index is also weighted, with the weightings based upon macroinvertebrate tolerance of various extents of in-channel dryness. At least, notionally, DELHI offers additional insights into the effect of drought on instream habitat and macroinvertebrates. When comparing LIFE and DELHI, Chadd *et al.* (2017) observed differences in response; however, application was restricted to a synthetic drought only. Consideration in the context of the wider coupled modelling framework could serve to provide new insights for locations which are known to be particularly drought-stressed, or projected to be in the future. Presently, DELHI is not abundance-weighted, therefore such work would be best undertaken, only following the development of a second iteration.

5.2 FLOW AS THE MASTER VARIABLE

Flow is considered the master variable, representing the dominant organising factor of instream ecology (Poff *et al*., 1997). Whilst true, flow alone is not sufficient to maintain river health (Poff, 2018). Whilst there have been limited applications of environmental flows in practice (Arthington *et al*., 2018), Poff (2018) highlight that the beneficial outcomes of a number of recent studies have been somewhat compromised. For example, as a result of sediment depletion or temperature alteration. The authors conclude that accounting for these confounding factors represents one, of many, important challenges still facing environmental flows science.

Therefore, this is not something that could be accounted for in the development of the coupled modelling framework. The methodology for establishing the (hydroecological) component model may, however, be adjusted as the necessary advancements are made, in order to account for these additional factors, without compromising robustness or minimising uncertainty.

5.3 CROSS-SECTORAL IMPACTS

The coupled modelling framework developed in this thesis focuses exclusively on environmental flows; the wider socio-economic context is not considered. The literature indicates that this siloed approach is not atypical of climate change impact assessments (Burkett *et al.*, 2014; Harrison *et al.*, 2016; Rosenzweig *et al.*, 2017; Sušnik *et al.*, 2018). Such a limited perspective may lead to over- or under-estimation of climate change impacts and hence poor decision-making (Harrison *et al.*, 2016). This is illustrated through an example from Pastor *et al.* (2019), exploring the linkages between water and food (in)security for a high emissions scenario. Presently, approximately 70% of freshwater abstraction is used for irrigation, with irrigated agriculture accounting for around 40% of global food production. Climate change is projected to exacerbate these pressures, with a reduction in crop yields of up to 80%. With increases in population, water demand and development pressures projected well into the future (Vörösmarty *et al.*, 2010), the impact of climate change will not be experienced in isolation.

There is, therefore, a clear need for adaptation planning that is robust to change in climate and socio-economic sectors (Burkett *et al.*, 2014). This may be achieved through loose coupling (on or offline) of impact models in order to explore linkages, interactions, and feedbacks. The longest established cross-sectoral intercomparison study is the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP). As in the Coupled Model Intercomparison Project, ISI-MIP brings together a suite of models under a set of protocols, ensuring consistency and enabling comparison; online and offline coupling of the models allows for consideration of cross-sectoral impacts. Presently, ISI-MIP brings together 28 impact models from across five sectors (Rosenzweig *et al.*, 2017). Despite the vital importance of rivers & freshwater, and the widely acknowledged need for environmental flows, ISI-MIP literature does not comment on environmental flow requirements[6].

Current signs suggest that, as environmental flows research begins to take account of climate change impacts, this will be addressed in due course. Certainly, the revised

[6] Based on a Scopus and Web of Science search on 22-01-2020 with the search terms {{"environmental flows"} OR {"e-flows"} OR {"eflows"}} AND {{"ISI-MIP"} OR {"ISIMIP"}}.

definition of environmental flows (Arthington *et al.*, 2018) acknowledges the importance of socio-economic sectors. To best explore the impacts and uncertainty, the resultant inter-comparison and cross-sectoral analysis would require consideration of a number of coupled hydroecological-hydrological models. The work in this thesis represents one possible route towards determining hydroecological projections.

Rosenzweig *et al.* (2017), and references therein, state that the uncertainty arising from impact models is often larger than that from climate models. An inter-comparison study would facilitate a more in-depth analysis of uncertainty, which would establish whether this is true of coupled hydroecological-hydrological models. Following Visser-Quinn *et al.*, (2019a), Hingray and Saïd's (2014) quasi-ergodic analysis of variance approach could be applied to partition the sources of uncertainty. The method is based on a quasi-ergodic assumption: after a sufficiently long time period, it is assumed that all possible states are captured. A noise-free-signal is determined per modelling chain (for example, emissions scenario-climate model-hydrological model-hydroecological model); analysis of variance (ANOVA) allows for the partitioning of the total uncertainty in terms of the relative contribution of each source. In doing so, it is possible to identify the main sources of uncertainty, and thus, direct the research where it is most needed. For example, Visser-Quinn *et al* (2019a) identified hydrological models as the largest source of variability, at times exceeding 80% of total variance (239 UK catchments forced under the RCP 8.5 emissions scenario; modelling chain of 5 global climate models and 3 hydrological models). It is clear that, future applications incorporating QE-ANOVA represents an opportunity to gain some very valuable insights.

Initially, the effort entailed for such work might seem prohibitive. However, Rosenzweig *et al.* (2017) highlights that inter-comparison studies generally require minimal budgetary resources – participation is entirely voluntary. They state that the main body of work lies in the establishment of simulation protocols, ensuring consistency across sectoral impact models.

CHAPTER 7. CONCLUSIONS

1. RESEARCH AIM

Pressures in excess of the capacity of a river to resist and adapt lead to damage and degradation of the ecosystem (Lake, 2013). This in turn impairs the river's functionality and ability to provide the vital goods and services upon which we depend. At the outset, this thesis established that, globally, rivers are under threat, with pressures stemming from changes in land use, urbanisation and irrigation, to name but a few (Vörösmarty *et al*., 2010). In response, this saw the emergence of the environmental flow movement. The provision of these environmental flows is intended to support the healthy functioning of riverine ecosystems, benefitting humans and non-humans alike (Arthington *et al*., 2018).

To date, such interventions have been limited (Arthington *et al*., 2018). The need only grows more urgent in the face of both increasing water (in)security, and a changing climate. A fact reflected in the Global Action Agenda appending the new Brisbane Declaration. The actionable recommendations look to practically advance environmental flow science. Specifically, an increased understanding of the hydroecological relationship, and the impact of climate change, is deemed essential to ensure the development of effective adaptation and mitigation measures.

It is for the reasons above that this thesis looked to improve current understanding of hydroecological response to climate change. This was to be determined through the development of a coupled modelling framework. The refinement of established methodologies represented a significant portion of the work undertaken, with the following requirements identified:

- Climate change is expected to see a rise in the frequency and severity of hydrological extremes. Delays in hydroecological response have been observed but limitedly accounted for. With this possible loss in recovery time, a need is emerging to account for this potential delay in hydroecological response;
- To illicit the hydroecological projections, the hydrological impact must first be understood. This is achieved through a hydrological model, forced with projections

of the changed climate. This hydrological model should focus not on hydrograph mimicry, but rather the replication of ecologically relevant hydrological signatures. Current methods appear inadequate and require optimisation.

To allow for more meaningful conclusions, the development of the framework took an uncommonly holistic approach to uncertainty. Application to the River Nar served to complete the framework development. In facilitating the determination of quantitative hydroecological projections, the overarching aim of this thesis is considered to be achieved.

2. SCIENTIFIC CONTRIBUTION OF THE WORK

Here follow some reflections on the contribution this work has made. This begins with the incidental outcomes – the improvements made to the methodologies used to derive the component models:

- **Hydroecological modelling**
  - Lag in hydroecological response has been hypothesised for more than a decade (Boulton, 2003; Wood and Armitage, 2004; Wright *et al*., 2004; Durance and Ormerod, 2007). The work in this thesis elicited three pertinent insights: (1) it is possible to account for this lag in hydroecological modelling; (2) this is achievably simple through the addition of time-offset; and (3), initially assumed to be a phenomenon exclusive to groundwater-fed rivers (Clarke and Dunbar, 2005; Visser *et al*., 2017), the results indicate delays in response across a range of flow regimes;
  - At the outset, the review of the start-of-the-art established that there is no established practice for accounting for uncertainty in hydroecological modelling. Enabling a truer representation of a complex reality, the work in the second publication (Visser *et al.*, 2018) addresses this significant shortfall in current practice without hugely demanding additional load. Cognitive bias appears as a potential limiting factor with regards to the benefits (Whittingham *et al*., 2006); however, this is an issue which may be addressed, with time.

- **Hydrological modelling**
    - The modified covariance approach appears capable of addressing many of the key challenges facing the replication of ecologically relevant hydrological signatures. This includes the explicit consideration (in a quantified manner) of hydroecological modelling outcomes. Tuning the hydrological model in this way represents a much needed advancement (Pool *et al*., 2017);
    - This work clearly illustrates that hydrological models are capable of replicating a suite of ecologically relevant hydrological indicators (ER HIs) – poor performance and consistency is not an inherent limitation of hydrological models. Though, this does raise the question whether this improvement was a product of the method, the explicit inclusion of the ER HIs, or both. Further work is necessary to make this more general conclusion.

With regards to the scientific contribution of the main output of this thesis, the coupled modelling framework represents the first approach (known to the author) capable of eliciting quantitative hydroecological projections. The revised Brisbane Declaration highlights the urgent need for frameworks such as this for the development of more informed management decisions. Visser *et al*. (2019b) highlighted that there may be a previously unknown degree of flexibility in environmental flow requirements – for the principal case study, immediately preceding winter flows were shown to offset negative impacts in preceding seasons and years. Armed with information such as this, water managers could potentially prioritise water for irrigation during periods of summer drought.

The supplementary publication (Visser *et al*., 2019a) highlighted some additional insights which may be gained through application of the framework.

- The potential to (qualitatively) explore the implications for ecosystem functionality under climate change. Ecosystem functionality has implications for resilience as well as being essential to the provision of ecosystem services;
- The results suggested that the impacts of climate change may be felt as early as the 2030s (2021-2050): these impacts may, then, be felt in the near, rather than

the far, future. (Recall, this finding is based on the assumption of stationarity, as discussed in *Chapter 6. Discussion*)

Critically, it is the focus of uncertainty which sets this work apart. The burden of uncertainty assessment, as is significantly reduced: the heavy lifting is already taken care of. Component models are optimised to minimise uncertainty; the user / modeller is then provided with the supportive information needed to guide the actual application. Additionally, by placing it at the centre of the framework, this work should serve to further promote uncertainty assessment.

Whilst direct adoption of the framework is possible, it was highlighted in the discussion that the associated workload may represent a practical limitation. However, it is important to remember that research in this area is in its infancy – a fact highlighted by the recently revised Brisbane Declaration.

Reaffirming what was said in Visser *et al.* (2019a), the work in this thesis represents a beginning. The principal value of this work lies in the advancement in understanding, which in turn can, and should, enable further practical developments. Here follows a brief overview of the potential avenues for further research made available:

- The framework development and example application were for a single case study. Hydroecological modelling and hydrological modelling are often undertaken using a regime- or regional-based spatial framework. In a similar manner, the coupled modelling framework should be readily transferrable and applicable. Such generic projections of the impact of climate change on hydroecological response might thus be used to plan wider adaption measured. Further work is necessary to confirm this assumption;
- Intercomparison projects, such as CMIP (Coupled Model Intercomparison Project) and ISI-MIP (Inter-Sectoral Impact Model Intercomparison Project), highlight the importance of developing a range of approaches in pursuit of answers to the same question. By looking at the problem from multiple angles, it becomes possible to explore uncertainty further and direct future research. The framework developed in this thesis can thus be thought of as representing one such way of looking at

the hydroecological impacts of climate change – it should valuably inform, and complement, such shared research efforts.

3. LIMITATIONS AND SCOPE FOR FURTHER RESEARCH

The ecological data requirements, coupled with a mismatch in the co-location of sampling sites, is a significant limiting factor in the field of hydroecology (Monk *et al.*, 2006; Knight *et al.*, 2008). Consequently, the principal obstacle to the implementation of the coupled hydroecological modelling framework is data availability. This may, in part, be resolved through application at the regional level or by flow regime type. Further work is necessary to confirm this.

The assumption of stationarity represents an additional limiting factor in this work. In *Chapter 6. Discussion – 4.2 Non-stationarity*, it is established that, at present, it is not possible to account for non-stationarity in natural systems. Thus, it can be said that this is an inherent limitation of most, if not all, research of a similar nature.

With regards to scope for further research, three areas of interest are identified: (1) application of the framework using a drought-focussed biotic index; (2) consideration of environmental controls, beyond flow; for example, geomorphology or temperature; (3) consideration of the wider socio-economic context through cross-sectoral intercomparison. The latter of these is potentially the most relevant, being essential to adaptation planning that is robust to change in both climate and socio-economic sectors. Indeed, the need for such research is highlighted in the revised Brisbane Declaration (Arthington *et al.*, 2018):

> *"Environmental flows describe the quantity, timing, and quality of freshwater flows and levels necessary to sustain aquatic ecosystems which, in turn, support human cultures, economies, sustainable livelihoods, and well-being".*

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4. CONCLUDING REMARKS

Overall, this research has demonstrated the ability to account for the hydroecological impact of climate change in a quantitative manner. This work has in turn enabled advancements in the fields of hydroecological and hydrological modelling. The relevance of the work is particularly highlighted through publication in a range of high-impact academic journals. The work in this thesis can be summed up as an exciting first step under the new agenda.

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APPENDIX A. HYDROECOLOGICAL MODELLING

A.1. LOTIC-INVERTEBRATE INDEX FOR FLOW EVALUATION

Macroinvertebrates are collected as part of routine biomonitoring. Flow groups, based on known ecological flow associations (Table A.1), are determined from score sheets provided by the Freshwater Biological Association (FBA, 2006); taxa may be scored at the Family or Species level. Taxa are then categorised by log abundance, detailed in Table A.2. The flow group and abundance category are then used to determine a flow score as per Table A.3. The LIFE score represents the sum of these flow scores, divided by the number of scoring taxa:

$$LIFE = \frac{\sum f_s}{n}$$

where f_s is the taxa flow score and n the number of taxa.

Table A-1. LIFE flow groups, reproduced from Extence *et al.* (1999).

Group	Ecological flow association	Mean current velocity
I	Taxa primarily associated with rapid flows	Typically > 100 cm/s
II	Taxa primarily associated with moderate to fast flows	Typically 20 – 100 cm/s
III	Taxa primarily associated with slow to sluggish flows	Typically < 20 cm/s
IV	Taxa primarily associated with flowing (usually slow) and standing waters	-
V	Taxa primarily associated with standing waters	-
VI	Taxa frequently associated with drying or drought impacted sites	-

Table A-2. LIFE abundance categories, reproduced from Extence *et al.* (1999).

Category	Estimated number of individuals in sample
A	1 – 9
B	10 – 99
C	100 – 999
D	1000 – 9999
E	10000+

Table A-3. LIFE flow scoring matrix, reproduced from Extence *et al.* (1999).

Flow group		Abundance categories			
		A	B	C	D/E
I	Rapid	9	10	11	12
II	Moderate/fast	8	9	10	11
III	Slow/sluggish	7	7	7	7
IV	Flowing/standing	6	5	4	3
V	Standing	5	4	3	2
VI	Drought resistant	4	3	2	1

A.2. SUITE OF ECOLOGICALLY RELEVANT HYDROLOGICAL INDICATORS

Table A-4. Suite of ecologically relevant hydrological indicators considered in this thesis. Indicators in bold were included in hydroecological models in either *Chapter 3 – 7. Validation* or Publication 3. *Primary sources: Monk et al. (2006) and Olden and Poff (2003). Secondary sources: 1, Hughes and James (1989); 2, (Richards, 1989); 3, Poff and Ward (1989); 4, Biggs (1990); 5, Jowett and Duncan (1990); 6, Poff (1996); 7, Richter et al. (1996); 8, Clausen and Biggs (1997); 9, Richter et al. (1997); 10, Puckridge et al. (1998); 11, Richter et al. (1998); 12, Clausen and Biggs (2000); 13, Clausen et al. (2000); and 14, Wood et al. (2001).*

#	Facet-aspect	Indicator name	Units	Description	Source
1	M-A	Mn	m^3/s	Mean daily average flow.	1; 2; 3
2	M-A	Sum	m^3	Total volume of flow.	Monk et al. (2006)
3	M-A	Rng	m^3/s	Range; the variability in daily average flow.	Monk et al. (2006)
4	**M-A**	**IQR**	**m^3/s**	**Interquartile range; the variability in daily average flows.**	This thesis
5	M-A	SD	-	Standard deviation; the variability in daily average flow.	Monk et al. (2006)
6	M-A	Var	-	Coefficient of variance; the variability of daily average flow.	1; 2; 3; 5; 6
7	**M-A**	**logQVar**	**-**	**Coefficient of variation of the log-transformed flows corresponding to the 5, 10, 15, 20, ……, 80, 95, 90, 95 percentiles.**	8
8	M-A	Sk	-	Skewness; the degree to which the mean is affected by extreme events relative to the median.	1; 2; 3

9	M-A	Sk100	-	Skewness; the degree to which the range is affected by extreme events relative to the median.	10
10	M-A	Sk50	-	Skewness; the degree to which the interquartile range is affected by extreme events relative to the median.	10
11	M-A	SkRel	m^3/s	Relative skewness; the scale of the skew relative to the median.	7
12	M-A	10R90	-	Characterisation of lows and highs; ratio of the 10th and 90th percentiles in daily average flow.	8
13	M-A	20R80	-	Characterisation of moderate lows and highs; ratio of the 20th and 80th percentiles in daily average flow.	8
14	M-A	25R75	-	Characterisation of moderate lows and highs; ratio of the 25th and 75th percentiles in daily average flow.	8
15	**M-A**	**10R90Log**	**-**	**Characterisation of lows and highs; ratio of the 10th and 90th percentiles of log-transformed daily average flow.**	8
16	M-A	20R80Log	-	Characterisation of moderate lows and highs; ratio of the 20th and 80th percentiles of log-transformed daily average flow.	8
17	M-A	25R75Log	-	Characterisation of moderate lows and highs; ratio of the 25th and 75th percentiles of log-transformed daily average flow.	8
18	M-A	Q01Q50	-	Characterisation of high flows; one percent exceedance flow relative to the median.	This thesis
19	**M-A**	**Q05Q50**	**-**	**Characterisation of high flows; five percent exceedance flow relative to the median.**	This thesis
20	M-A	Q10Q50	-	Characterisation of high flows; ten percent exceedance flow relative to the median.	8; 12; 13
21	M-A	Q20Q50	-	Characterisation of high flows; twenty percent exceedance flow relative to the median.	8; 12; 13

22	M-A	Q25Q50	-	Characterisation of high flows; twenty five percent exceedance flow relative to the median.	8; 12; 13
23	M-A	Q30Q50	-	Characterisation of moderate high flows; thirty percent exceedance flow relative to the median.	8; 12; 13
24	M-A	Q40Q50	-	Characterisation of moderate high flows; forty percent exceedance flow relative to the median.	8; 12; 13
25	M-A	Q50	m^3/s	Median daily average flow.	1; 2; 3
26	**M-A**	**Q60Q50**	**-**	**Characterisation of moderate low flows; sixty percent exceedance flow relative to the median.**	8; 12; 13
27	**M-A**	**Q70Q50**	**-**	**Characterisation of moderate low flows; seventy percent exceedance flow relative to the median.**	8; 12; 13
28	M-A	Q75Q50	-	Characterisation of low flows; seventy five percent exceedance flow relative to the median.	8; 12; 13
29	**M-A**	**Q80Q50**	**-**	**Characterisation of low flows; eighty percent exceedance flow relative to the median.**	8; 12; 13
30	**M-A**	**Q90Q50**	**-**	**Characterisation of low flows; ninety percent exceedance flow relative to the median.**	8; 12; 13
31	M-A	Q95Q50	-	Characterisation of low flows; ninety five percent exceedance flow relative to the median.	This thesis
32	M-A	Q99Q50	-	Characterisation of low flows; ninety nine percent exceedance flow relative to the median.	This thesis
33	M-H	Max	m^3/s	Maximum flow.	12
34	M-H	MaxQ50	-	Relative maximum flow; maximum flow divided by the median.	12
35	M-H	Q01	-	One percent flow exceedance.	This thesis

36	M-H	MaxMonthly Med	-	Mean of the maximum monthly flow relative to the median flow value for the entire flow record.	3
37	M-H	MaxMonthly Var	-	Variability of maximum monthly flows.	4
38	M-H	MaxMonthly LogVar	-	Variability of log-transformed maximum monthly flows.	4
39	**M-L**	**Min**	**m^3/s**	**Minimum flow.**	12
40	**M-L**	**MinQ50**	**-**	**Relative minimum flow; minimum flow divided by the median.**	12
41	M-L	Q99	-	Ninety nine percent flow exceedance.	This thesis
42	**M-L**	**MinMonthly Med**	**-**	**Mean of the minimum monthly flow relative to the median flow value for the entire flow record.**	4
43	**M-L**	**MinMonthly Var**	**-**	**Variability of minimum monthly flows.**	4
44	M-L	MinMonthly LogVar	-	Variability of log-transformed minimum monthly flows.	4
45	M-L	BFI	-	Baseflow index, i.e. average annual ratio of the lowest daily discharge to the mean daily discharge.	12; 13; 14
46	F-H	PlsQ25	-	High flow pulse count; the number of flow events where flows are above a threshold equal to the twenty five percent exceedance flow value for the entire flow record.	9; 10; 11
47	F-H	PlsQ50	-	Flow pulse count; the number of flow events where flows are above a threshold equal to the median flow value for the entire flow record.	9; 10; 11
48	F-L	PlsQ75	-	Low flow pulse count; the number of flow events where flows falls below a threshold equal to the seventy five percent exceedance flow value for the entire flow record.	9; 10; 11

49	D-H	Mn7Max	m^3/s	Seasonal maximum of 7-day moving average flow.	This thesis
50	D-H	Mn7Max Q50	-	Seasonal maximum of 7-day moving average flow relative to the median.	This thesis
51	**D-H**	**Mn30Max Q50**	**-**	**Seasonal maximum of 30-day moving average flow relative to the median.**	**This thesis**
52	D-H	PlsDurQ25	days	Total duration of flow pulses above twenty five percent exceedance flow.	This thesis
54	**D-H**	**PlsDurQ25 Mn**	**days**	**Average duration of flow pulses above twenty five percent exceedance flow.**	**This thesis**
54	D-H	PlsDurQ25 Var	days	Variability in flow pulses above twenty five percent exceedance flow.	This thesis
55	D-H	PlsDurQ50	days	Total duration of flow pulses above fifty percent exceedance flow.	This thesis
56	**D-H**	**PlsDurQ50 Mn**	**days**	**Average duration of flow pulses above fifty percent exceedance flow.**	**9; 10; 11**
57	D-H	PlsDurQ50 Var	days	Variability in flow pulses above fifty percent exceedance flow.	This thesis
58	D-L	Mn7Min	m^3/s	Seasonal minimum of 7-day moving average flow.	This thesis
59	D-L	Mn7MinQ50	-	Seasonal minimum of 7-day moving average flow relative to the median.	This thesis
60	D-L	Mn30Min Q50	-	Seasonal minimum of 30-day moving average flow relative to the median.	This thesis
61	D-L	PlsDurQ75	days	Total duration of flow pulses below seventy five percent exceedance flow.	This thesis
62	D-L	PlsDurQ75 Mn	days	Average duration of flow pulses below seventy five percent exceedance flow.	9; 10; 11
63	D-L	PlsDurQ75 Var	days	Variability in flow pulses below seventy five percent exceedance flow.	This thesis
64	R-A	fallMn	m^3/s	Fall rate; mean change in flow for days in which the change is negative.	9; 10; 11

65	R-A	fallVar	-	Variability in fall rate; variability in flow for days in which the change is negative.	9; 10; 11
66	R-A	fallLogMed	m^3/s	Log fall rate; the median change in log-transformed flow, for days in which the change is negative.	This thesis
67	**R-A**	**riseMn**	**m^3/s**	**Rise rate; mean change in flow for days in which the change is positive.**	**9; 10; 11**
68	R-A	riseVar	-	Variability in rise rate; variability in flow for days in which the change is positive.	9; 10; 11
69	R-A	riseLogMed	m^3/s	Log rise rate; the median change in log-transformed flow, for days in which the change is negative.	This thesis
70	R-A	RevNeg	-	Number of negative changes in flow from one day to the next.	11
71	**R-A**	**RevPos**	**-**	**Number of positive changes in flow from one day to the next.**	**11**
72	R-A	RevVar	-	Variability in the number of negative and positive changes in flow from one day to the next.	11
73	T-A	JDRng	-	Difference in the Julian date of the maximum and minimum daily average flow.	1; 2; 3; 5; 6
74	**T-H**	**JDMax**	**-**	**Julian date of the 1-day maximum daily average flow.**	**3; 9; 10; 11**
75	**T-H**	**Mn7MaxJD**	**-**	**Julian date of the mean 7-day maximum flow.**	**This thesis**
76	**T-H**	**JDMaxMn or Mn30MaxJD**	**-**	**Julian date of the mean 30-day maximum flow.**	**Monk et al. (2006)**
77	**T-H**	**Mn90MaxJD**	**-**	**Julian date of the mean 90-day maximum flow.**	**This thesis**
78	T-H	JDMaxSD	-	Standard deviation in the Julian date of the seven 1-day maximum daily average flow.	Monk et al. (2006)

79	T-H	JDMaxVar	-	Variability in the Julian date of the seven 1-day maximum daily average flow.	This thesis
80	T-L	JDMin	-	Julian date of the 1-day minimum daily average flow.	3; 9; 10; 11
81	T-L	Mn7MinJD	-	Julian date of the mean 7-day minimum flow.	This thesis
82	**T-L**	**JDMinMn or Mn30MinJD**	**-**	**Julian date of the mean 30-day minimum flow.**	**This thesis**
83	T-L	Mn90MinJD	-	Julian date of the mean 90-day minimum flow.	This thesis
84	**T-L**	**JDMinSD**	**-**	**Standard deviation in the Julian date of the seven 1-day minimum daily average flow.**	**Monk et al. (2006)**
85	T-L	JDMinVar	-	Variability in the Julian date of the seven 1-day minimum daily average flow.	This thesis

A.3. HYDROECOLOGICAL MODEL STRUCTURES

Table A-5. Linear equations representing the hydroecological model structures derived in *Chapter 3 – 7. Validation.* See Table A-1 for definitions of each ecologically relevant hydrological indicator.

Case study	*Hydroecological model equation*
Tarland Burn	$LIFE = 0.70\ IQR_{w,\ t-1} + 0.39\ Mn30MaxQ50_{s,\ t-0} + 0.004\ Mn7MaxJD_{w,\ t-0} - 31.4\ Q80Q50_{w,\ t-1} + 22.9\ Q90Q50_{w,\ t-1} - 0.0096\ JDMinSD_{w,\ t-1} + 2.47$
River Trent	$LIFE = 0.005\ Mn30MaxJD_{w,\ t-0} + 0.016\ Mn90MaxJD_{s,\ t-0} + 1.03\ MinMonthlyMed_{s,\ t-0} + 13.6\ MinMonthlyVar_{s,\ t-1} - 1.79\ Q60Q50_{s,\ t-1} - 0.51\ BFI_{s,\ t-1} + 4.78$
River Ribble	$LIFE = -0.00079\ JDMax_{w,\ t-0} - 0.0072\ Mn90MaxJD_{w,\ t-0} + 0.03\ PlsDurQ25Mn_{w,\ t-0} + 0.76\ Q60Q50_{w,\ t-0} + 8.07$
River Nar	$LIFE = 0.07\ 10R90Log_{w,\ t-0} - 0.04\ RevPos_{s,\ t-1} + 0.93\ Q80Q50_{s,\ t-0} - 0.5\ logQVar_{s,\ t-1} + 0.3\ Q90Q50_{s,\ t-1} + 0.11\ Q70Q50_{s,\ t-1} + 0.07\ RiseMn_{w,\ t-0} + 7.64$
River Thrushel	$LIFE = -0.001\ JDMinMn_{w,\ t-1} - 2.20\ MinQ50_{s,\ t-0} - 0.04\ Q05Q50_{s,\ t-0} - 0.016\ PlsDurQ50Mn_{s,\ t-1} + 5.22\ Min_{s,\ t-1} + 7.10$

APPENDIX B. SUPPLEMENTARY PUBLICATION

Visser, A., Beevers, L., & Patidar, S. (2019). The Impact of Climate Change on Hydroecological Response in Chalk Streams. *Water*, 11(3), 1-19. doi: 10.3390/w11030596

water

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Article

The Impact of Climate Change on Hydroecological Response in Chalk Streams

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Abstract: Climate change represents a major threat to lotic freshwater ecosystems and their ability to support the provision of ecosystem services. England's chalk streams are in a poor state of health, with significant concerns regarding their resilience, the ability to adapt, under a changing climate. This paper aims to quantify the effect of climate change on hydroecological response for the River Nar, south-east England. To this end, we apply a coupled hydrological and hydroecological modelling framework, with the UK probabilistic climate projections 2009 (UKCP09) weather generator serving as input (CMIP3 A1B high emissions scenario, 2021 to the end-of-century). The results indicate a minimal change in the long-term mean hydroecological response over this period. In terms of interannual variability, the median hydroecological response is subject to increased uncertainty, whilst lower probability extremes are *virtually certain* to become more homogeneous (assuming a high emissions scenario). A functional matrix, relating species-level macroinvertebrate functional flow preferences to functional food groups reveals that, on the baseline, under extreme conditions, key groups are underrepresented. To date, despite this limited range, the River Nar has been able to adapt to extreme events due to interannual variation. In the future, this variation is greatly reduced, raising real concerns over the resilience of the river ecosystem, and chalk ecosystems more generally, under climate change.

Keywords: climate change impact; ecosystem functionality; freshwater ecosystems; UKCP09; hydroecological impact; river health

1. Introduction

Under the Convention on Biological Diversity, biodiversity is defined as the variability among living organisms, within & between species and ecosystems [1,2]. Within the public sphere, reasons for preserving biodiversity are, frequently, purely aesthetic, cultural and economic [3]. Critically, the societal cost of biodiversity loss, in terms of ecosystem functionality, may be severe. In recent years, significant progress has been made towards understanding this dependency [2,3]; if not universal, broad consensus points include [4]:

- Increased diversity fosters greater productivity of ecosystem functions;
- The diversity-stability hypothesis [5] states that biodiversity introduces redundancy in the system, thereby introducing both resistance and resilience to environmental change;
- The loss of certain species may have keystone effects which cascade through the ecosystem [6]; for example, Woodward, et al. [7] observed that the presence and absence of freshwater shrimp (*Gammarus pulex*), a dominant predator in chalk streams, exerted a strong influence on detrital processing rates.

Termed the freshwater paradox, freshwaters are disproportionately rich in biodiversity [8]. Rivers and streams cover approximately 0.58% of the world's (nonglacial) surface [9], yet up to 7% of species make freshwaters their home [10,11]. For humans, freshwater is considered the most essential natural resource [12]. In addition to water supply, rivers support prosperity, health, and well-being through the provision of ecosystem services; examples include hydro-hazard regulation, water purification and recreation [13]. Our need for freshwater has seen a rapid decline in freshwater biodiversity; in a 2016 World Wildlife Fund (WWF; see Table A1 for definitions of all abbreviations used) report [14] it was estimated that, between 1970 and 2012, freshwater biodiversity declined by 81%, more than double that of terrestrial and marine combined. Figure 1 illustrates the impact of environmental change on biodiversity, ecosystem functionality and hence the provision of the vital ecosystem services upon which we depend.

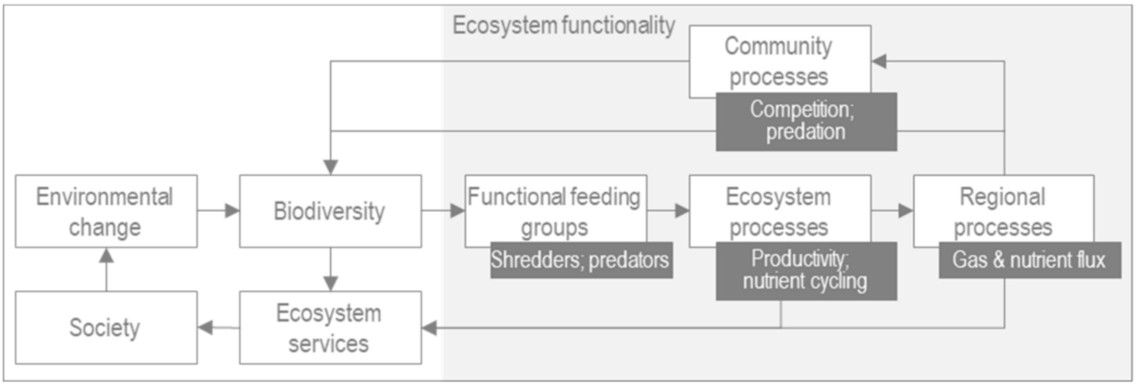

Figure 1. Conceptual diagram of the linkages between biodiversity, ecosystem functionality (inset represent examples of functions) and ecosystem services. Based on Chapin et al., 1997 [6] and Cardinale et al., 2012 [4].

The functional composition of the macroinvertebrate community is a major determinant of ecosystem functionality [15]. As consumers at intermediate trophic levels, macroinvertebrates exert strong bottom-up and top-down controls [16]. The above, coupled with their sensitivity to environmental change, makes macroinvertebrates ideal biological and functional indicators [17–19].

Macroinvertebrate functional feeding groups describe their consumption of resources [20], for example, scrapers consume foodstuffs such as algae which are attached to substrate. It is this processing of organic matter which facilitates essential ecosystem processes such as productivity and nutrient cycling [4,6], which in turn supports processes at the regional level. Understanding how the composition of the macroinvertebrate community changes helps to understand the ecological processes in a river, thereby aiding understanding for the purposes of conservation and restoration [21], as well as adaptation to environmental change [22]; the latter being the focus in this study. Flow is widely acknowledged as a major determinant of the health of the river ecosystem (for example, see [23–27]). Data-driven numerical models are used to link flow and hydroecological response in order to understand the instream response to changes in flow [28]. Arguably, the term river health is more useful for interpretation than hydroecological response [29]; hereafter, the term river health should be considered interchangeable with hydroecological response.

Chalk streams provide a steady flow of cool, clear and nutrient-rich water whose gravel channels support uniquely "diverse and fecund ecosystems" [30]. Such streams are famous amongst anglers due to the high levels of fish production that chalk waters are able to support (relative to other river types) [31]. Charles Rangeley-Wilson [30] describes the importance of England's 224 chalk streams as analogous to such biodiversity hotspots as the Great Barrier Reef and equatorial rainforests. Indeed, these streams are (almost entirely) unique to Southern England, with only a handful located in Northern France [30]. The result of a legacy of historical physical modifications—e.g., for systems of water mills and meadows for irrigation [32] as well as more recent fisheries management [33]—75% of English chalk-streams were designated 'heavily modified water bodies' under the 2008–2012 River Habitat Surveys [30]. Following on from their first report on the state of England's chalk streams a decade prior, the Environment Agency (EA) and WWF-UK concluded that English chalk streams "remain in a shocking state of health" [30,34]. With increasing water demand and climatic variability (e.g., increased hydro-hazards [35,36]), there are significant questions as to the long-term sustainability of this water resource [6,30,37–41]. This is of particular concern given the chalk aquifer provides 70% of the public drinking water in south-east England [30].

The aim of this paper is to quantify the effect of climate change on the river health of a chalk stream. Methods investigating hydroecological response have, typically, been qualitative in nature or quantitative with limited scope, whilst the effect of uncertainty (e.g., parameter, structural, emissions scenario) is rarely considered [42]. To address this research gap, the author's proposed a coupled hydrological and hydroecological modelling framework [42]. The framework was developed using an English chalk stream, the River Nar in Norfolk, where the coupled model was run for a single scenario, CMIP3 SRES A1B high emissions (Coupled Model Intercomparison Project; Special Report on Emissions Scenarios) and 30-year time slice (2041–2070). This paper considers both change in river health over time (from the 2030s to the end of century) as well as the implications for ecosystem functionality. To this end, we consider the same case study river, eliminating the need for model calibration. The UK probabilistic climate projections 2009 (UKCP09) weather generator serves as input to the coupled model; specifically, the high emissions scenario (CMIP3 SRES B1). The results focus on the 99–100% probability, consistent with the Intergovernmental Panel on Climate Change's (IPCC) definition of a virtually certain outcome [43]. The wider implications for chalk streams and groundwater-fed rivers more generally are also reflected upon.

2. Case Study Catchment—River Nar

The River Nar, Norfolk, East Anglia (Figure 2) is classified as both chalk and fenland river [44]. For this reason, the river and 180 ha of adjacent land, was designated a Site of Special Scientific Interest (SSSI) in 1992 [33,45], one of only eight chalk streams to be designated as such [30]. In this paper, the focus is on the 24 km chalk river which encompasses an area of 153.3 km^2 from the (principal) source at Mileham (TG895194) to the Marham gauging station (TF723119) [46]. Hereafter, all references to the River Nar refer to this chalk reach only.

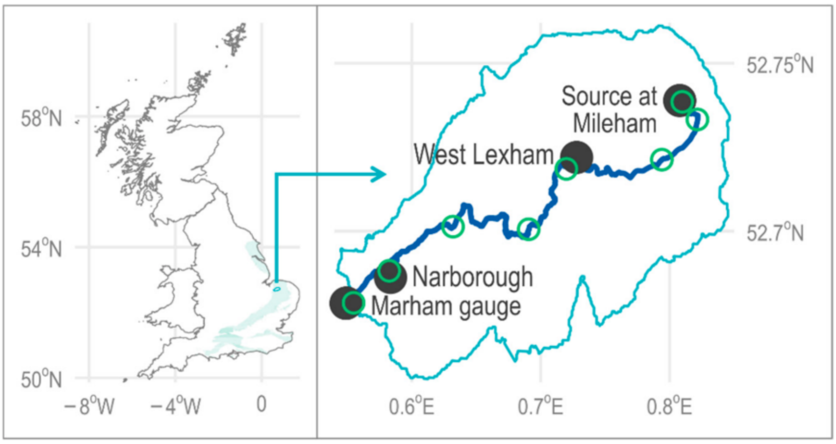

Figure 2. Left: Location of English chalk aquifers (shaded) and the case study river catchment (arrow). **Right:** River Nar catchment map; key locations and Environment Agency macroinvertebrate sampling sites are indicated (green).

2.1. Hydrology

Flow in the chalk valley is sustained by six springs between West Lexham and Narford Lake (nr. Narborough; Figure 2) [44]. With a baseflow index of 0.91, the hydrology of the river Nar is consistent with that of a classic chalk stream [44]. Typified by a highly seasonal flow regime, aquifer recharge occurs in the autumn months at the start of the hydrologic year (identified as October-November-December; see Figure 3) with flow peaking in January and February (Figure 3). These high flows may see reconnection to floodplain habitats [33]. With a runoff coefficient of 0.35 (1961–1990), flow in the River Nar is indicated as moderately sensitive to change in precipitation [47].

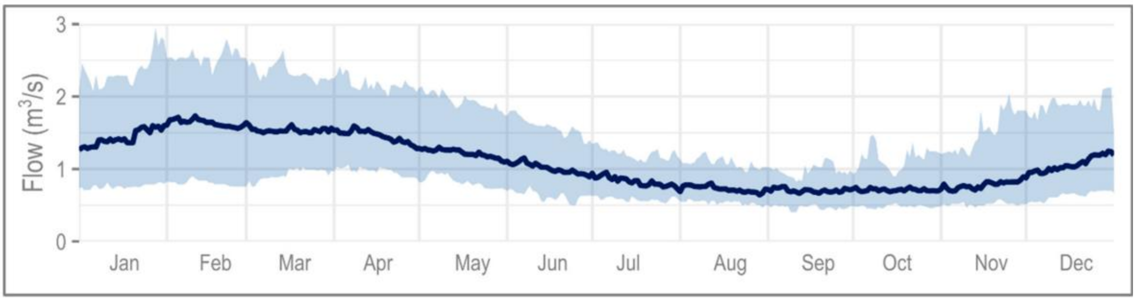

Figure 3. Daily median flow recorded at the Marham gauge (1961–1990); the shaded area represents the flow envelope of daily Q90 to Q10 flows. Data source: NRFA, 2018 [46].

2.2. Hydrogeomorphological Pressures

The ecological potential of the River Nar is limited to the extent that it is deemed "technically infeasible" for the river to meet the ecological requirements of the Water Framework Directive (WFD) [33,48]. The principle reason is the long history of physical modifications, including Medieval navigation systems, domesday mills, ornamental estate lakes, and most recently, agricultural drainage [33]; only the latter remains functional, providing socio-economic benefits to the catchment. As a low-energy chalk stream, peak flows in the Nar are insufficient to reshape the channel, thus intervention is the only means through which the river might realise its ecological potential. The already fragile state of the river is further exacerbated by sediment ingress as well as over-abstraction for the service of public water supply, fish farms and spray irrigation [30,33,48].

2.3. Biodiversity

In chalk streams, peaks in macroinvertebrate activity typically occur in spring (April-May-June where flow begins to recede following winter; hatching season) and autumn (October-November-December; when detritus (food) enters the river system) [32]. Fishing is vital to communities along the River Nar [49,50], as well as chalk streams more generally [30].

Chalk streams are renowned for their abundance of flora and fauna; the high water table and flooding help to support a number of wetland habitats, on the River Nar these include water meadows & pastures, fen wetlands and wet woodlands [49]. From 1993–2017, a total of 188 macroinvertebrate species were observed across 21 orders (see also Table 1); samples were collected by the EA at the eight sites detailed in Figure 2. A total of 12 species of dragonfly *(Odonata)* have been recorded, described as an "outstanding assemblage" in the SSSI designation [49]. Key species such as otters and ecosystem engineers, water voles, have been widely observed in recent years [30,33].

Table 1. Number of macroinvertebrate species, grouped by order, observed in the spring season (April-May-June) in the River Nar.

Order, *Latin Name* (Common Name)	**No. Species per Order**
Coleoptera (Beetles)	35
Diptera (True flies)	3
Ephemeroptera (Mayfly)	17
Gastropoda c. (Snails and slugs)	19
Hemiptera (True bugs)	14
Odonata (Dragonfly and damselfly)	8
Trichoptera (Caddisfly)	52
Other (13 orders)	40
Total	**188**

3. Methods

This paper considers the impact of climate change on river health, hydroecological response, and the implications for ecosystem functionality, in chalk streams. This response is determined through application of a quantitative coupled model [42] with the River Nar serving as case study. Probabilistic climate change projections, from the UKCP09 weather generator, serve as input to the coupled hydrological-hydroecological model. To put this into context, the proxies for river health and ecosystem functionality are first introduced in Section 3.1. An overview of the applied methodology is provided below in Figure 4.

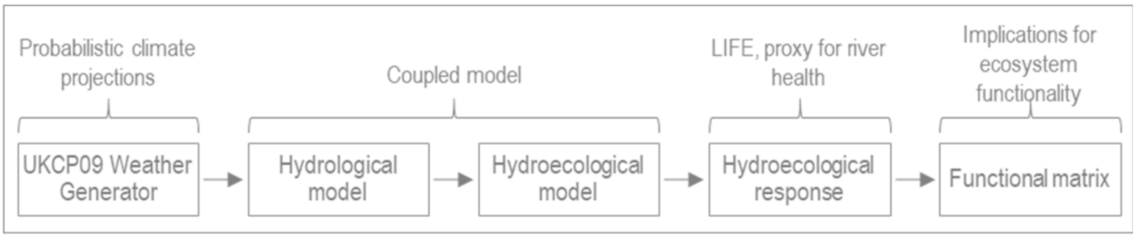

Figure 4. Overview of methodological approach.

3.1. River Health and Ecosystem Functionality

In this study, the lotic-invertebrate index for flow evaluation (LIFE) [51] serves as the proxy for river health. The LIFE index combines functional flow preferences with the (log) abundance of each taxa to determine flow scores, *fs* (see Appendix A, Figure A1 for a matrix summary of this relationship). The LIFE score is thus determined as:

$$\text{LIFE} = \frac{\sum fs}{n} \tag{1}$$

where the numerator is the sum of the *fs* per taxa, and n is the total number of taxa. Lower flow scores, and by extension LIFE scores, are associated with limited flow and standing water, whilst high scores are an indication of rapid flows.

Chapin et al. (1997) [6] stated that no two species are ecologically redundant, it is the diversity within macroinvertebrate functional feeding groups that ensures the resilience of the freshwater ecosystem. Specifically, variation in environmental preferences, such as flow, ensures that a decrease in abundance of one species will be compensated by an increase in a functionally similar species. The importance of diversity, in the context of climate change, and as the freshwater ecosystem responds to more extreme flood and drought events, cannot be understated. A range of represented traits ensures the productivity of the ecosystem.

The impact of pressures, such as climate change, on the functionality of freshwater ecosystems has been limitedly explored, for example [52,53]. Here, we create a matrix of functional flow preferences and feeding groups (defined in Table A2) using species level macroinvertebrate data collected by the EA at eight sites on the River Nar (Figure 2) from 1993 to 2014 (spring season, April-May-June; $8 * 22 * 1 = 176$ samples) [54]. This 'matrix' highlights which aspects of ecosystem functionality (to date) are most vulnerable to changes in flow. We consider the matrix in the context of the hydroecological projections to elucidate the possible impacts of climate change.

3.2. Climate Projections

The UKCP09 probabilistic climate projections, a 25 km grid-square resolution Perturbed Physics Ensemble (HadCM3/HadSM3), serve as the input to the coupled hydrological-hydroecological model. The weather generator was used to produce synthetic stochastic time series at a daily timestep, 5 km grid-square resolution, of climate variables based on observed climate statistics and change factors. The weather generator product was chosen due to its ability to represent climatic variability [55,56], allowing low probability events, vital to ecosystem functionality [57], to be captured more effectively [58]. The climate models upon which the weather generator is based are known for their ineffective simulation of climatic extremes, particularly with regards to precipitation [59]; to address this, the tails of the UKCP09 climate projections are clipped (<5% and >95% probability) [60].

The objective of this study is to explore the change in hydroecological response over time. A range of the CMIP3/SRES scenarios are used in UKCP09: low (B1), medium (A1B) and high (B1); see Figure A2 for scenario specific increase in CO_2 emissions. The high emissions scenario was selected due to concerns over the influence that high magnitude change points (Figure A2, highlighted in red) might have on the change signal over time.

Data requests for the required climate variables, precipitation and potential evapotranspiration, were submitted using the UKCP09 web-based portal (http://ukclimateprojections-ui.metoffice.gov.uk/ui/admin/login.php); as of 31 December 2018, data is accessed through the Centre for Environmental Data Analysis (CEDA) archives. The full range of projections (10,000) were considered for each 30-year time slice. As per UKCP09 recommendations, linear bias correction of the climate variables was applied bimonthly (where necessary) [61]. The projections indicate increases in precipitation and potential evapotranspiration in both winter and summer across the three time slices (Figure A3).

3.3. Coupled Hydrological-Hydroecological Modelling Framework

The case study river was used by the authors [42] in the development of the coupled hydrological-hydroecological modelling framework. The hydrological and hydroecological models were thus parameterised and validated in the course of the example application, thereby eliminating the need to parameterise and validate the models in this study. To provide context, Sections 3.3.1 and 3.3.2 below provide a brief overview of the hydrological and hydroecological models.

3.3.1. Hydrological Model

The four-parameter lumped hydrological model GR4J (Genie Rural a 4 parametres Journalier) [62] was applied using the R package airGR [63]. In summary, the soil moisture accounting model sees: (1) water enter a production store with capacity x1 mm; (2) the water is divided into two flow components, routed through unit hydrographs with time base x4 days; (3) a groundwater exchange term, x2 mm/day, acts upon one component of routed flow, whilst the other enters a routing store with capacity x3 mm; (4) flow in the river is the sum of these two routed flow components.

In the coupled modelling framework, the hydrological model is parameterised using a modified covariance approach which focuses explicitly on the replication of hydrological indicators. Hydrological indicators are used in an effort to improve simulation of the behaviour of the underlying catchment processes [64–66]. Under this approach, the covariance structure of the input (precipitation and potential evapotranspiration) and output (flow) time series are used to identify the region of parameter space which is best able to replicate the characteristics of the hydrological indicators.

The model was parameterised using data over a 54-year period (1961–2015) [42]. The capacity of the production (x1) and routing (x3) stores were estimated at 511 and 311 mm respectively; the time base for flow routing is approximately 1.17 days (x4). A positive groundwater exchange coefficient (x2) of 2.84 mm per day represents inflow from the chalk aquifer.

3.3.2. Hydroecological Model

A suite of ecologically relevant hydrological indicators, reflecting Richter's (1996) [67] five facets of the flow regime (magnitude, frequency, duration, timing and rate of change) were considered. In light of seasonality in the flow regime (Figure 3), indicators were determined for both winter (October-November-December-January-February-March) and summer (April-May-June-July-August-September) seasons. Additionally, a one-year time-offset was introduced in order to account for previously observed delays in macroinvertebrate hydroecological response [28,68].

The hydroecological model is developed using multiple linear regression with an information theory approach. This information theory approach provides a measure of the statistical importance of each hydrological indicator (measure of the statistical weight of evidence for the inclusion of the index in the model) in addition to minimising and quantifying uncertainties (structural and parameter). For the structure of the hydroecological model and hydrological indicator definitions, see Equation (A1) and Table A3 in the Appendix A.

3.3.3. Analysis

There are no established methods for the analysis due to the relative novelty of the coupled modelling framework [42]. Accordingly, focus fell on the change in distribution of the hydroecological response. For comparison, the projections on the baseline and three future time slices are considered as discrete datasets, with the same methodological approach applied to each. The quantification of uncertainty is central to the application of the coupled modelling framework. To this end, lower and upper bounds of uncertainty where appropriate. Consistent with the IPCC terminology of a *virtually certain* outcome, we use the 99.5% confidence interval [42]. We consider both the aggregated (30-year time slice) and disaggregated (year-on-year) hydroecological response to ensure that the long-term and interannual trends are captured.

4. Results

The focus here is on comparison of the distribution of LIFE score, the proxy for river health, over the four time-periods. See Appendix A (Figure A1) for how to interpret LIFE scores relative to functional flow preference. To provide a general overview of the change over time, the long-term trends (aggregate 30-year time slices; Section 4.1) are presented first, followed by the interannual change (Section 4.2) to examine year-on-year variation. Finally, in Section 4.3, the functional matrix, relating functional flow preferences to feeding groups, is considered in the context of these hydroecological projections.

4.1. Long-Term Change

The probability density function (PDF; Figure 5) provides a visual representation of the LIFE score distribution for each time slice. The baseline distribution, 1961–1990, sees LIFE scores centered on ~7 (functional flow preference slow to sluggish). From the baseline to the 2030s, the reduction in this clustering coincides with an increase in LIFE scores, whilst the change from the 2030s to 2050s is less marked. The trend for increasing LIFE scores continues into the 2080s where the clustering of LIFE scores can be seen to increase again.

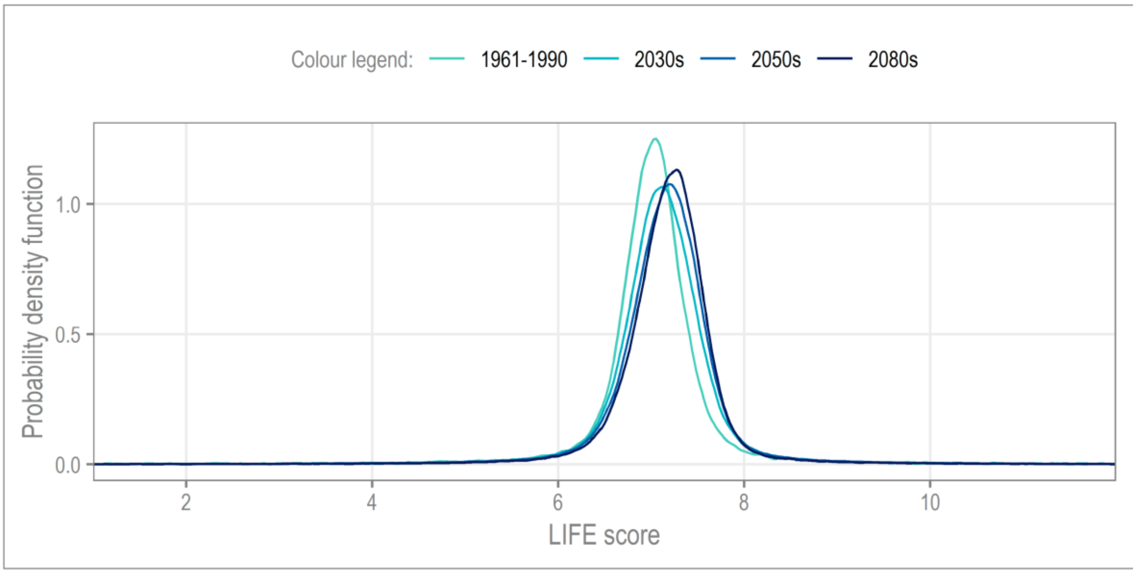

Figure 5. Distribution of lotic-invertebrate index for flow evaluation (LIFE; proxy for hydroecological response/river health) projections on the baseline and three futures.

To elucidate further, we consider the standard deviation, as well as the measures of distribution excess kurtosis and skewness (Table 2). The standard deviation reveals an initial increase in variance (2030s), with a subsequent decrease to below the baseline level by the 2080s, suggestive of a slight increase in low probability hydroecological responses by the end of the century. However, the difference across the time slices is relatively small, indicating a limited change in the central distribution of hydroecological response overall.

Table 2. Summary statistics of LIFE projections, proxy for hydroecological response or river health.

	1961–1990	2030s	2050s	2080s
Standard deviation	0.68	0.72	0.7	0.65
Excess kurtosis	12.43	9.75	10.57	12.9
Skewness	−0.86	−0.76	−0.83	−1

Note that for excess kurtosis and skewness, comparisons from baseline to future are not possible, due to differences in sample size (n = 1000 on baseline [69] p. 24). Excess kurtosis is a measure of the combined weight of the tails relative to the normal distribution; for example, a negative value means that more of the dataset is located in the tails than the normal distribution (note that kurtosis is often misinterpreted as a measure of peakedness [70]). Table 2 shows that, for all four time periods, the weight is not located in the tails (hence the observed clustering in Figure 5 previously). Table 2 shows that the change in kurtosis from the 2030s to 2050s, −0.07, is more than half that of the 2050s to 2080s, −0.17. Skewness, a measure of the symmetry in the distribution, shows that all four time-periods are right-skewed; here, the increase from 2050s to 2080s is almost 3 times that of 2030s to 2050s.

In summary, the aggregated projections indicate a very limited change in the mean hydroecological response under climate change. However, Table 2 does highlight that, by the end-of-century, there may be a restructuring of the macroinvertebrate community response to low-probability events. Note that, the smaller scale of change observed between the 2030s to 2050s may be explained by the overlap between these two time slices (2041–2050).

4.2. Interannual Variability

The long-term mean may mask significant changes in the interannual variability of hydroecological response. Figure 6 describes vertical cross-sections (at specific quantiles) through annual PDFs of LIFE score; the error bars represent the range of values possible for a *virtually certain* outcome (99.5% probability, based on the available information). Whilst the y-axis for each quantile does vary, it is clear that, perhaps counter to expectation, that the greatest uncertainty surrounds projections of the median response, and across the 5th to 95th quantiles more generally. Next, we consider the change per cross-section (Figure 6), starting with the median, interquartile range (IQR) and finally the tails of the distribution.

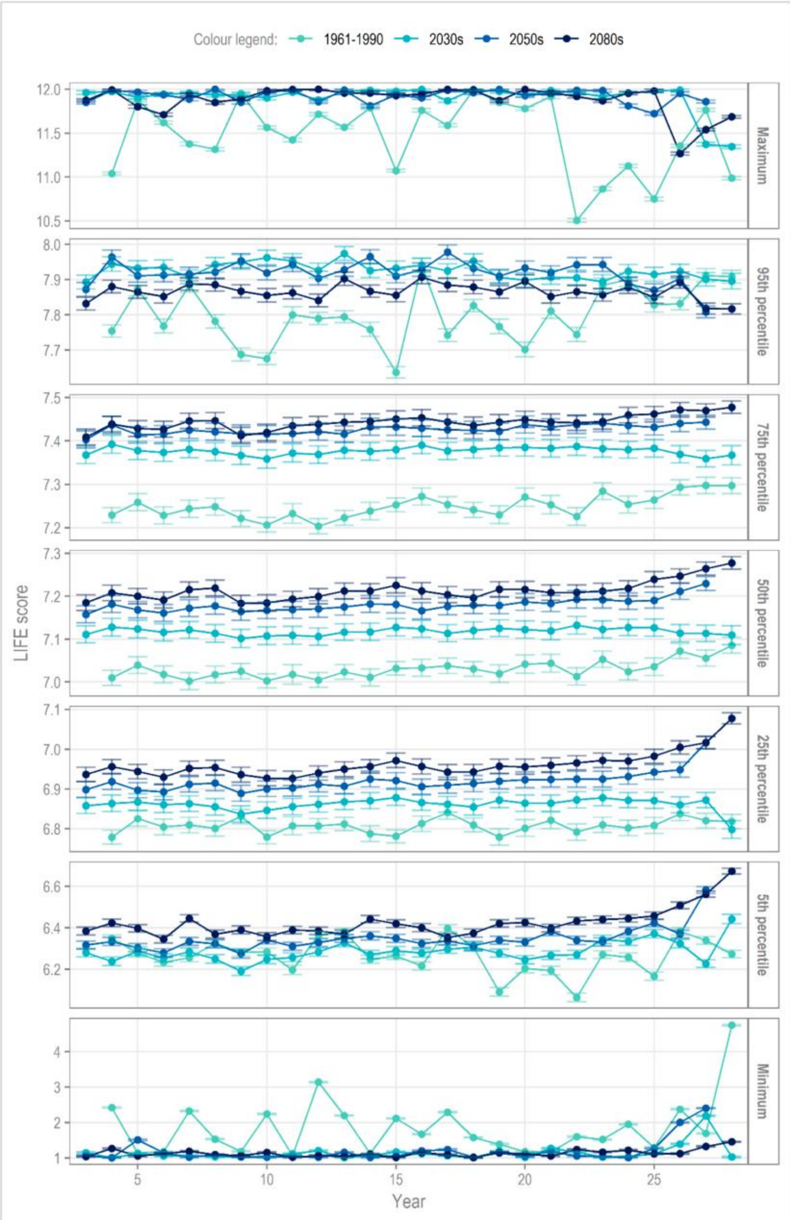

Figure 6. Vertical cross-sections (at specific quantiles) through the PDFs of annual LIFE score; the error bars represent the range of *virtually certain* outcomes. The x-axis refers to years 3–28 in each time period (1961–1990, 2030s, 2050s and 2080s), offset is due to the consideration of lag in hydroecological response in the hydroecological model; the y-axis scale is not fixed.

The small shift in median LIFE scores (by time slice) indicates the increased presence of taxa with higher flow scores (Equation (1)), though the variability of LIFE score remains broadly unchanged. At the 75th percentile, a large change occurs between baseline and the 2030s, while the change from the 2050s to 2080s are almost negligible. At the other end of the IQR (25th percentile), the increase in LIFE scores is approximately linear until the end-of the century. As for the 50th percentile, the variation in interannual LIFE scores, per time slice, remains constant.

We now look to the tails of the distribution, essentially the hydroecological response to lower probability extreme events. At the 95th percentile, the change in variance relative to the baseline stands out (Figure 6), with Table 3 revealing that the reduction in variance may reach 92% as early as the 2030s. At the other end of the spectrum, the 5th percentile, the reduction in variance, although reduced, is still high at −65%.

Table 3. Percentage change in variance relative to the baseline, per time slice, at the tails of the annual probability density functions (PDFs).

	2030s	2050s	2080s
95th percentile	−92	−81	−91
5th percentile	−65	−52	−31
Maximum	−84	−97	−83
Minimum	−92	−84	−98

Changes in the maximum and minimum hydroecological responses are marked, affecting not only variance, but also LIFE score. For the maximum, on the baseline, LIFE scores can be seen to vary from 10.5 to the maximum of 12. However, the projections for all three future time slices show a plateau at LIFE scores of 12; a varied response becomes almost impossible. At the minimum, the same phenomenon is observed, with LIFE scores plateauing to a value of 1 with almost no variance. Further, the reduction in range is more notable than for the maximum.

Examination of the year-on-year change in hydroecological response provides further clarification on the subtle changes observed over the long-term (Section 4.1). Figure 6 and Table 3 also highlight the timing of a major change in hydroecological response could occur as early as the 2030s, 2021–2050. This suggests that a major high or low flow event, in the very near future, could result in a hydroecological response very different to the past (baseline period), where there was the probability of a more varied response. By considering the associated uncertainty, we can be *virtually certain* of this outcome, based on the available information. Given a potentially highly limited period of preparation, this is of concern for the future health of the River Nar.

4.3. Functional Matrix

This paper introduces the functional matrix, Figure 7, relating species-level macroinvertebrate functional flow preferences to functional food groups. See Appendix A for definitions. Figure 7 is determined based on observed macroinvertebrate data collected in spring (April-May-June), and thus reflects average conditions between 1993 and 2014. In terms of functional feeding group, only a limited number of species with a range of flow preferences are observed, e.g., scrapers which may tolerate anything from very low to rapid flows. The matrix highlights several functional feeding group traits potentially unrepresented under extreme conditions. The data covers periods of very high and low flows, ensuring that response to extremes are captured. For example, the available time series began in 1993, at the end of the 1989–1992 supra-seasonal drought where groundwater levels fell to their lowest in over 90 years [71]; inadequate groundwater supplies, coupled with increased water abstraction due to the ongoing drought, saw summer and winter Q95 flow fall below 0.16 and 0.19 m^3/s, respectively [46].

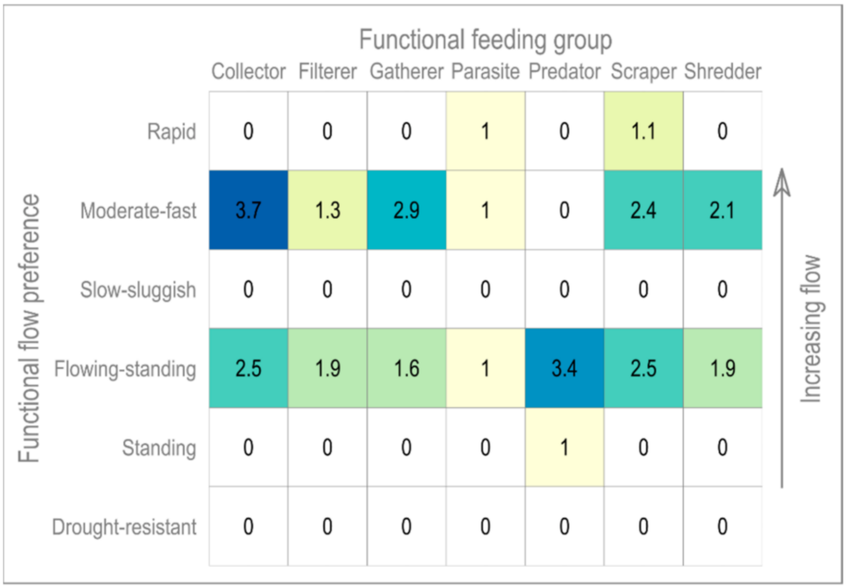

Figure 7. Functional matrix relating functional feeding groups to functional flow preferences at the species level. The values indicate the spring annual average number of species fulfilling a given niche. For example, there are, on average, 2.4 species observed in the upper Nar each spring who fulfill the role of scraper and prefer moderate to fast flows.

In the context of the hydroecological projections, we see an increase in the probability of both very high and low LIFE scores. Looking to Figure A1 in the Appendix A, we can see that LIFE scores below 5/4 are dominated by taxa with preferences for standing waters or drought, and for the highest scores, it is taxa that prefer rapid flows that dominate. Looking then to the functional matrix, it is evident that almost none of the taxa previously observed in the River Nar would be able to perform their functional roles, long-term, under such environmental conditions. In the short-term, the ecosystem has been able to successfully recover, consistent with findings by Wood and Petts [72]. Wood and Petts found in their 1994 study that the impact of drought on chalk streams was, in part, determined by the health of the river ecosystem prior to the drought event. With the projections indicating a reduction in future biodiversity, the concomitant decrease in macroinvertebrate adaptability may significantly impact the resilience of the riverine system.

5. Discussion

5.1. Impact of Climate Change

Freshwater biodiversity is a major determinant of ecosystem functionality and hence the provision of ecosystem services. Despite this, freshwater biodiversity is declining rapidly around the globe. Coupled with the impact of climate change, there are growing concerns about the long-term sustainability of our water resources.

In this study, we looked at the River Nar, a south-England chalk stream. Using a novel coupled modelling approach, we project how the health of the river may change over time, under a high emissions scenario. The LIFE index served as a proxy for river health. The results showed that, across all three future time slices, interannual variation in LIFE scores is reduced to such an extent that they, essentially, 'flatline'. Over the IQR, the most common hydroecological responses, this change is relatively gradually across the time slices. The change in response at the tails of the distribution is much more marked, with an almost complete loss of variability at both the high and low end of the spectrum by the 2030s.

The overall trend indicates an increased probability and magnitude of extreme responses, with less internal variability. This level of change relative to the baseline conditions has major implications for the structure of the macroinvertebrate community, and hence on ecosystem functionality. The functional matrix, Figure 7, revealed that all functional flow preferences are only met at intermediate flows (LIFE scores range from approximately 6 to 8). Under more extreme conditions, they are effectively 'knocked out'.

To date, the river system has been able to recover from extreme events, indeed, these events may be necessary to ensure the long-term functionality of the ecosystem, acting as a form of "natural reset" [73,74]. However, these responses occurred under a more heterogenous macroinvertebrate community which was adapted to such conditions. With the results indicating a more homogeneous community structure in the future, this may no longer be the case in the very near future. Further, increases in duration of hydro-hazards as reported by Collet et al., 2018 [35] (CMIP3 SRES A1B) and Visser et al., in review [36] (CMIP5 RCP2.6 and RCP8.5) could exacerbate threats to an increasingly vulnerable riverine ecosystem.

5.2. Uncertainty

To ensure the validity of the projections, the quantification of uncertainty was central to the application of the coupled modelling framework. To this end, this study utilised the UKCP09 probabilistic climate projections and the UKCP09 weather generator, allowing for the effective capture of lower probability events. To further ensure confidence in the results, a 99.5% probability level was considered. In terms of interannual variability, the bounds of uncertainty are largest for the median and interquartile range, and the greatest confidence lies within the tails of the distribution. Consequently, it is possible to state that a 98% reduction in the variance of hydroecological response by the end of the century is *virtually certain*.

5.3. Enhancing and Encouraging Ecological Resilience in Chalk Streams

To our knowledge, this paper represents the first time that quantitative projections of hydroecological response over time have been available. With impacts of climate change being manifest in the river expected as early as 2021 (2030s time slice), the outlook for the River Nar is not promising. A large part of this low resilience may be attributed to the pressures on the river. The River Nar is not alone in this, the State of England's Chalk Streams [30] reporting that, overall, English chalk streams are in a poor state of health, largely for similar reasons. Therefore, whilst this study has focussed on the River Nar specifically, these findings are likely to be more widely applicable to the 200+ chalk streams in England. However, this is not and should not be considered a foregone conclusion, as there remains the opportunity to intervene via improved river management.

Plans for restoration of the River Nar began with the 2010 River Nar Restoration Strategy, with a total of 27 restoration initiatives planned for completion before 2027 [33]. (Note that, in the development of the hydroecological model in Visser et al. [42] and the functional matrix in this study, pre-restoration data was used, 1993–2014.) As the project is completed, and more data is available, this work also presents an opportunity for further study into the effect restoration has on river health and climate change adaptation.

For chalk streams more broadly, a number of positive advancements have been made in recent years. In recognition of the poor condition of chalk streams, there is a drive by Natural England for the reestablishment of a national chalk stream forum [30]; though as of 2018 progress is yet to manifest. The 2014 amendment to the Water Act means that abstraction licence holders on longer have the right to compensation when environmental flow limits are applied. Consequently, water companies are now looking towards investment in measures which ensure water efficiency and thus an overall reduction in abstraction [30].

The fertile chemistry of chalk streams supports their rich ecology and biodiversity, making these systems highly sensitive to changes in nutrient balance. Consequently, management options such as compensation flows and river transfers are unsuitable in these catchments [49]. A pertinent outcome of the project (EPSRC 1786424), of which this study is part, is the finding that, for the River Nar, up to two years of antecedent flows influence the health of the river; additionally, antecedent winter flows (t-0) are the main determinant of which aspects of the flow regime govern the hydroecological response [42]. See Table A3 for indicator definitions. A summer with high variation in flows could have a significant negative impact on the river two years later; however, a high ratio of Q80 to Q50 flows in the following summer may serve to mitigate these effects. The influence of these antecedent flows become irrelevant when the winter index 10R90Log has either very high or low flow values (dominates LIFE score due to the log nature of the index). These findings indicate a previously unknown degree of flexibility in how the water in the catchment may be utilised. In combination with dynamic environmental flow limits, this represents an opportunity to incorporate with water trading [75,76]. In this way, both the quantity and timing of abstraction may be better managed. Initial scoping studies [75,76] indicated that, for brown trout (*Salmo Trutta*) and mayfly (family *Baetidae*), water trading is unlikely to have a significant impact on habitat availability. However, the study did not consider the importance of this natural variability on the adaptability of the ecosystems or the potential effects of climate change.

6. Concluding Remarks

The aim of this paper was to quantify the effect of climate change on hydroecological response in terms of both long-term change and interannual variability. A coupled hydrological and hydroecological modelling framework was forced with UKCP09 high emissions (CMIP3 A1B) projections from 2021 to the end of century. The River Nar, a Norfolk chalk stream, served as the case study catchment. Whilst a minimal change in the long-term mean hydroecological response was projected, the results suggest the homogenization of hydroecological response at the tails of the distribution. At present, the River Nar is shown to be resilient to extreme events despite the absence of key functional groups. With interannual variability contributing to this resilience, the findings in this study raise real concerns over the long-term resilience of the river ecosystem. These new insights into the health of the River Nar, and chalk streams more generally, highlight the necessity of further study and the real need to for changed river management practices. Whilst this work has offered certain pertinent and timely conclusions on the health of the Nar (prior to restoration works), and by extension the chalk stream assemblage across England, it may also be understood as a beginning. The methods are practically applicable across the piece with regards to assessment of the impact of climate change on river health. Further, a better understanding of the River Nar may, and indeed must, facilitate management interventions to safeguard its health and future ecosystem functionality.

Author Contributions: A.V. developed the code, performed the data analysis and developed the concept of the functional matrix. A.V. prepared the manuscript whilst L.B. provided review and edits. Both L.B. and S.P. provided supervision.

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Conflicts of Interest: The authors have no conflicts of interest to declare.

Appendix A

Table A1. Definition of the abbreviated terms used in the text.

Abbreviation	Definition
CEDA	Centre for Environmental Data Analysis (UK)
CPOM	Coarse particulate organic matter
CMIP	Coupled Model Intercomparison Project
EA	Environment Agency (UK)
FPOM	Fine particulate organic matter
GR4J	Genie Rural a 4 parametres Journalier
IPCC	Intergovernmental Panel on Climate Change
IQR	Interquartile range
LIFE	Lotic-invertebrate index for flow evaluation
PDF	Probability density function
SSSI	Site of Special Scientific Interest (UK)
SRES	Special Report on Emissions Scenarios
UKCP09	UK Climate Projections 2009
WFD	Water Framework Directive (EU)
WWF	World Wildlife Fund

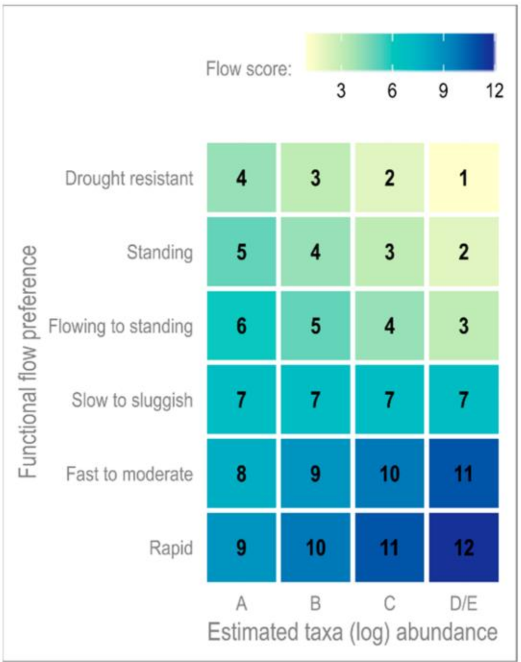

Figure A1. Matrix used to determine flow scores (*fs*) in the determination of LIFE scores.

Table A2. Description of the seven functional feeding groups considered. Aquatic food resources are classified by size: coarse and fine particulate organic matter (CPOM and FPOM respectively).

Functional Feeding Group	Description
Collector	A broad grouping generally capturing both filterers and gatherers.
Filterer	Filter suspended FPOM from the water column.
Gatherer	Gather FPOM settled on the substrate.
Parasite	Taxa which do not fit into other groups.
Predator	Carnivorous macroinvertebrates which prey on smaller invertebrates.
Scraper	Consumers of food sources attached to the substrate; e.g., algae and biofilm.
Shredder	Shred and consume plant material such as leaf litter and wood.

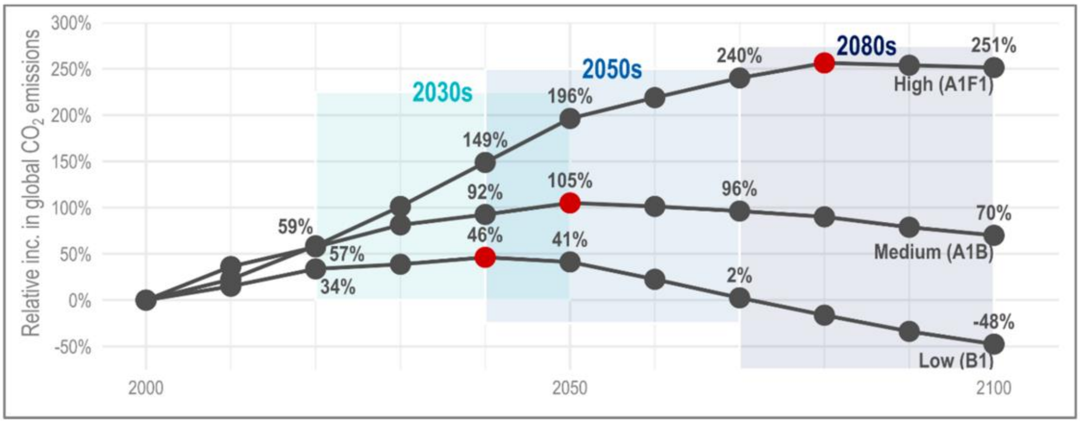

Figure A2. The relative (1961–1990 baseline) increase in global CO_2 emissions for the three scenarios in UKCP09. Three 30-year time slices are indicated through shading; note that there is some overlap in the 2030s and 2050s slices. Change points, where emissions begin to fall, are indicated in red.

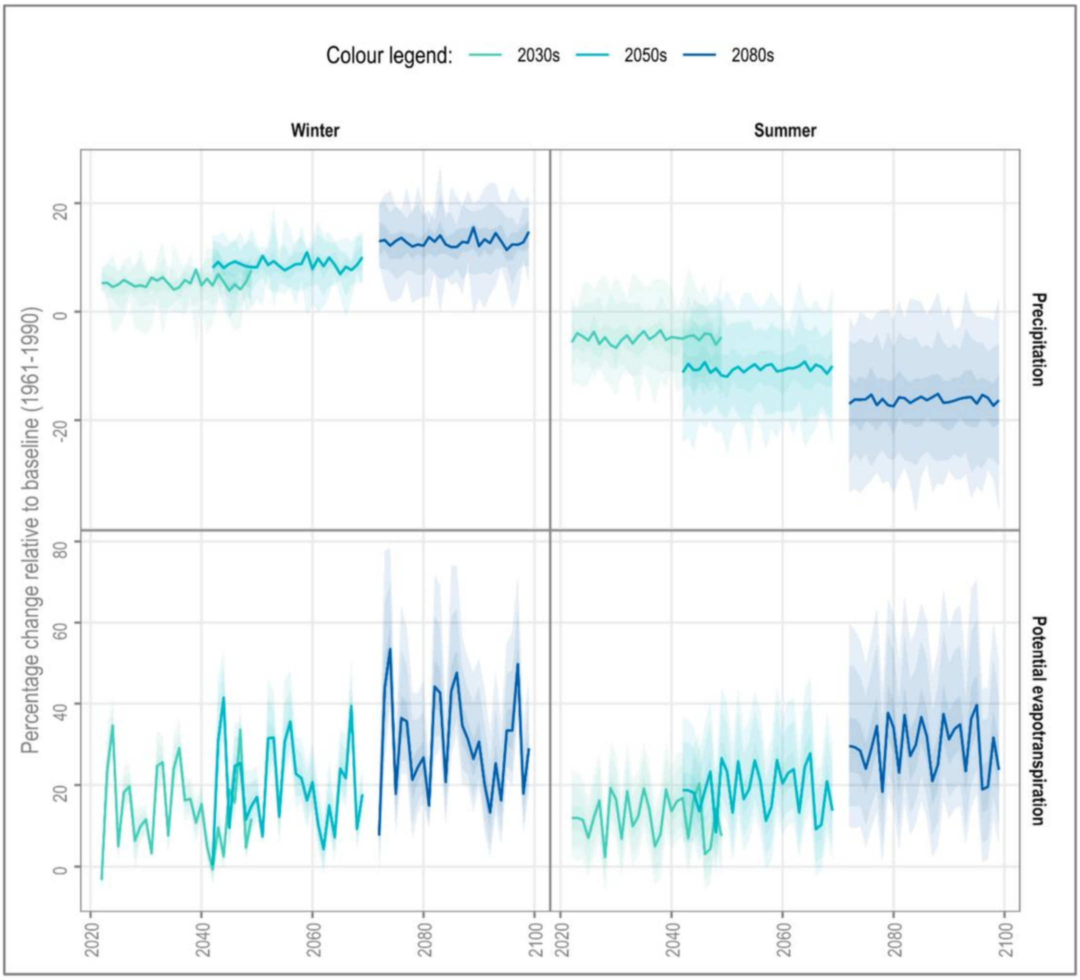

Figure A3. Mean percentage change for precipitation (top) and potential evapotranspiration (bottom) across each of the three time periods relative to the 1961–1990 baseline. The solid line indicates the mean, whilst the three envelopes indicate the: interquartile range (darkest), 5th and 95th percentiles (medium) and 1st and 99th percentiles (lightest).

$$\text{LIFE} = 0.07\ 10R90Log_{w,\ t-0} + 0.07riseMn_{w,t-0} + 0.93\ Q80Q50_{s,\ t-0} + 0.02\ Q90Q50_{s,\ t-0} \\ +0.3\ Q90Q50_{s,t-1} + 0.11\ Q70Q50_{s,t-1} - 0.04\ RevPos_{s,t-1} - 0.5logQVar_{s,t-1} \tag{A1}$$

Table A3. Description of the seven hydrological indicators in the hydroecological model (see Equation (A1)).

Index Name	Hydrological Season	Time-Offset	Unit	Description
$10R90Log_{w,t\text{-}0}$	Winter	t-0	-	Ratio of log-transformed low to high flows: log(P10)/log(P90). Log-transformation represents the log-normal distribution of flow.
$revPos_{s,t\text{-}1}$	Summer	t-1	days	Number of days when flow is increasing (positive reversals).
$Q80Q50_{s,t\text{-}0}$	Summer	t-0	-	Characterisation of moderate low flows; Q80 relative to the median.
$logQVar_{s,t\text{-}1}$	Summer	t-1	m^3s^{-1}	Variance in log flows.
$Q90Q50_{s,t\text{-}1}$	Summer	t-1	-	Characterisation of low flows; Q90 relative to the median.
$Q70Q50_{s,t\text{-}1}$	Summer	t-1	-	Characterisation of moderate low flows; Q70 relative to the median.
$riseMn_{w,t\text{-}0}$	Winter	t-0	m^3s^{-1}	Mean rise rate in flow.

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APPENDIX C. ERRATA

C-1 PUBLICATION 1

Visser, A., Beevers, L. and Patidar, S. (2017) 'Macro-invertebrate Community Response to Multi-annual Hydrological Indicators', *River Research and Applications*, 33(5), pp. 707–717. doi: 10.1002/rra.3125.

- Page 42 – Page 4 of publication
    - Right-hand side column
    - First paragraph under *Modelling and statistical analysis*
    - *"$p > 0.05$"* should read *"$p < 0.05$"*

C-2 PUBLICATION 2

Visser, A. G., Beevers, L. and Patidar, S. (2018) 'Complexity in hydroecological modelling: A comparison of stepwise selection and information theory', *River Research and Applications*, 34(8), pp. 1045–1056. doi: 10.1002/rra.3328.

- Page 57 – Page 4 of publication
    - Right-hand side column
    - Second line, missing citation: *Isbell, F., Calcagno, V., Hector, A., Connolly, J., Harpole, W. S., Reich, P. B., Scherer-Lorenzen, M., Schmid, B., Tilman, D., van Ruijven, J., Weigelt, A., Wilsey, B. J., Zavaleta, E. S. and Loreau, M. (2011) 'High plant diversity is needed to maintain ecosystem services', Nature, 477(7363), pp. 199–202. doi: 10.1038/nature10282*

C-3 PUBLICATION 4

Visser, A. G., Beevers, L. and Patidar, S. (2019) 'A coupled modelling framework to assess the hydroecological impact of climate change', *Environmental Modelling & Software*, 114(April 2019), pp. 12–28. doi: 10.1016/j.envsoft.2019.01.004.

- Page 126 – Page 15 of publication
    - Right-hand side column
    - Third paragraph under *2.2.2 Modified covariance approach, l*ine 7
    - *"A linear relationship..."* should read *"A log-linear relationship..."*
- Page 127 – Page 16 of publication
    - Right-hand side column
    - Third paragraph under *3.3 Stage 2 – Hydrological model*, line 3
    - *"from which the linear threshold"* should read *"from which the log-linear threshold"*
- Page 128 – Page 17 of publication
    - Left-hand side
    - First paragraph under *4.1.1 Underlying hydroecological processes*
    - Second last line
    - *"The negative sign of the HI riseMn indicates a preference for a low mean rise rate..."* should read *"The positive sign of the HI riseMn indicates a preference for a higher mean rise rate..."*