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Regulation of freshwater use to restore ecosystems resilience

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ABSTRACT

Concern about the impacts of water regulation upon the aquatic environment has led to increasingly stringent regulatory constraints on the quantity and timing of freshwater withdrawals. For the time being these regulatory constraints tend to be articulated in terms of limits upon withdrawals, partly because of limited knowledge of the condition and resilience of the aquatic ecosystems. A more sophisticated approach to regulation would be more directly related to indicators of ecological condition. Moreover, it would consider ecosystem response to climatic events not present in the historical record. In this paper we use a combination of empirical evidence of ecosystem condition with simulation to propose and test reductions to regulatory limits on river water withdrawals and downstream minimum flow requirements. The study uses multilevel linear regression to relate the Lotic-invertebrate Index for Flow Evaluation (LIFE) to antecedent flow statistics observed in the Lee catchment, England. The selected flow statistics included extreme low (Q90) and high (Q10) flows in the summer season (April-Sept), and the median flows observed in the winter season (Oct-Mar). The derived model is used to forecast the response of the macroinvertebrate index to future flow scenarios and demand forecasts, incorporating the uncertainties in ecosystem response. Simulation is used to evaluate the sensitivity of the indices to different regulatory limits. Results indicate that macroinvertebrate health will worsen under 21st Century climate conditions, and that the existing regulation policy must be modified to maintain historically observed LIFE scores into the future. The framework demonstrates how regulations could move from precautionary limits on withdrawals to an approach based on observations, forecasting and simulation, allowing planners to refine the trade-offs between river health and reliable water supply in the face of uncertainty.

1. Introduction

There is mounting evidence that hydrological alteration and riverine habitat degradation influence river ecosystems (WWF, 2018), with growing demand for water threatening 65% of river habitats (Vörösmarty et al., 2010). Globally, increased water withdrawals throughout the 20th and early 21st Century have left rivers fragmented (Biemans et al., 2011) and with reduced flows (Richter et al., 2003). In England, water withdrawal for public water supply has had a damaging effect on ecosystems, with an estimated 20% of rivers suffering from over-abstraction (Environment Agency, 2019a). Increased risk of ecosystem damage has led to 'opinion' driven implementation of precautionary regulatory thresholds (Klaar et al., 2014), which typically set limits and restrict the removal of water during periods of low flow. Whilst such schemes aim to sustain riverine ecosystems (Poff & Zimmerman, 2010), they fail to reflect the dynamism of ecosystems under shifting environmental regimes (Arthington et al., 2018). Moreover, very little has been done to

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explore the relationship of regulatory limits on water withdrawals to climatological, hydrological and demand side uncertainties inherent in water systems planning. For these reasons, practitioners and researchers alike have called for: (i) improvements in methodology to inform and support water management decisions (Stoffels et al., 2018); (ii) development of rigorous predictive science frameworks (Poff, 2018); and, (iii) recognition of risk in riverine management (Acreman et al., 2014a, 2014b).

To minimize the environmental impact of water withdrawals, it is imperative to understand the interaction between management decisions and riverine ecosystems. Traditional hydro-ecological studies have shown that different elements of the flow regime influence biotic community in river habitats (Acreman et al., 2014a, 2014b; Bunn & Arthington, 2002). Hydro-ecological relationships can be characterized using statistical associations between antecedent flow and macroinvertebrate indices (Monk et al., 2007, 2006); relationships which are then used to prescribe environmental flow thresholds for river reaches. Multi-level regression models (Dunbar et al., 2010a; 2010b), Principle Component Analysis (Clews & Ormerod, 2009; Worrall et al., 2014), ANOVA (Clews & Ormerod, 2010), and Generalized Linear Mixed Effects Models (England et al., 2019) have all been used to explore biotic responses to environmental change. These tools have proved successful in motivating decision makers (Kendy et al., 2012), with planners aiming to minimize flow alterations from the natural river condition (Olivares et al., 2015), or target flows to achieve specific ecological outcomes (Barbour et al., 2016; Basdekas et al., 2014).

Biomonitoring tools are commonly used within environmental flow studies to explore biotic response to changing abiotic conditions in river environments, providing key information for water managers, environmental authorities, and other practitioners (Mellado-Díaz et al., 2019). Macroinvertebrate indices (MI) such as Lotic Invertebrate index for Flow Evaluation (LIFE), Biological Monitoring Working Party score (BMWP), Whalley Hawkes Paisley Trigg metric (WHPT), and Proportion of Sediment-sensitive Invertebrates index (PSI) have been used to investigate historical change in river habitats. Previous work has used indices to evaluate the impact of invasive freshwater species on macroinvertebrates (Mathers et al., 2016), and explore the effects of riparian management on stream biota (Clews & Ormerod, 2010). Other investigations have explored macroinvertebrate response to drought (Chadd et al., 2017), and to river flowing, ponded, and drying states (England et al., 2019), revealing a strong negative relationship with the MIs and antecedent low flows. Elsewhere, MIs have been used to explore the impact of reservoir impoundment (Krajenbrink et al., 2019) and groundwater withdrawals (Westwood et al., 2017) on instream communities, with results highlighting the importance of careful catchment management. Finally, several studies have investigated the relationship between climate non-stationarity, historical extreme events, observed warming, and land use stressors on metrics of river health (Murdoch et al., 2020; Thompson et al., 2018).

Despite the density of studies which have investigated macroinvertebrate response to hydrological change, few have examined the

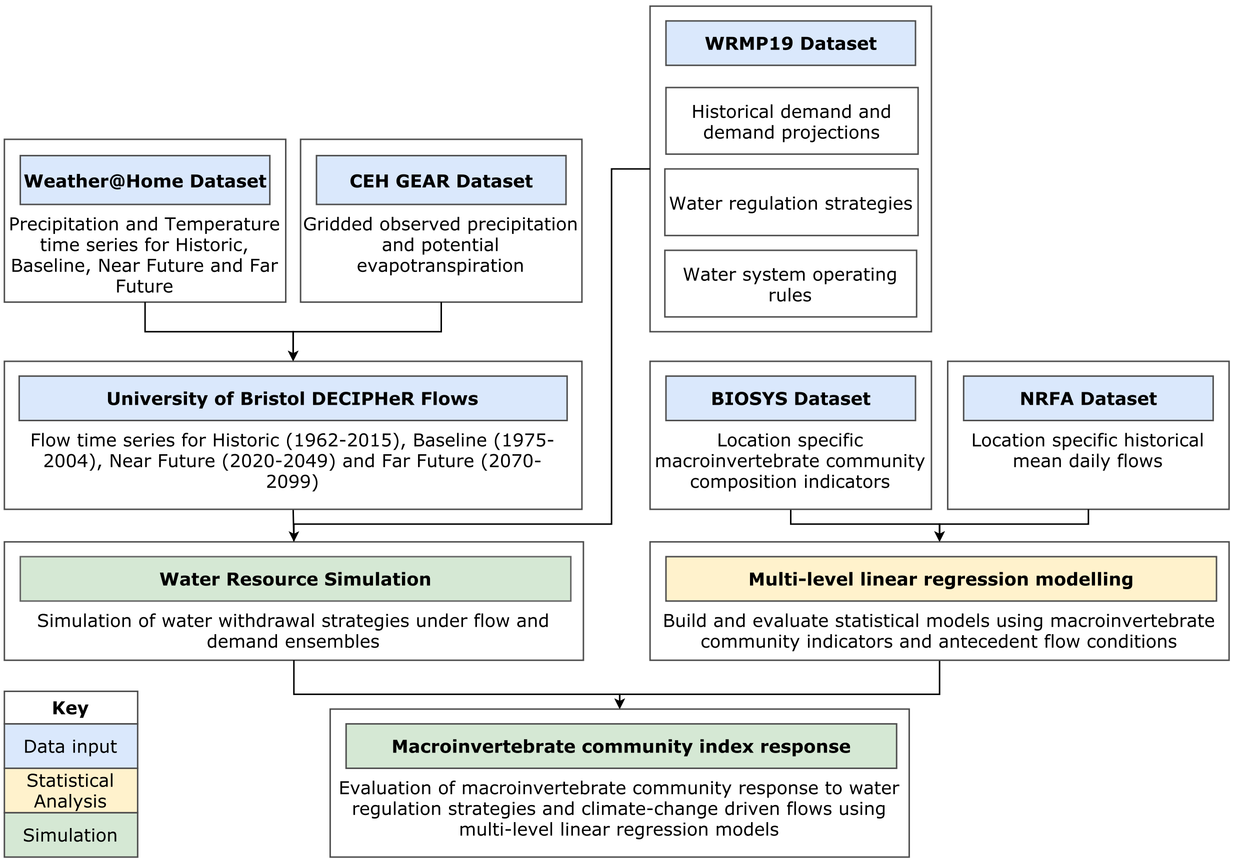

Fig. 1. Flowchart of the simulation and hydro-ecological modelling framework.

impact of future climate change and increased water demand on macroinvertebrate health. Visser et al. (2019) present one of the few studies that targets issue, by quantifying hydro-ecological response to 21st Century climate change. Their coupled hydrological-ecological framework used weather sequences from the UKCP09 climate projections to examine patterns in functional composition of macroinvertebrate community under a high emissions scenario. Results indicated that a shift away from baseline conditions and decreased inter-annual variability in flow are likely to impact the structure of macroinvertebrate communities and ecosystem functionality. Given this information, it is imperative to identify and implement adaptation actions that help to sustain freshwater ecosystems under 21st Century conditions.

This study presents a novel, coupled simulation and hydro-ecological modelling framework to examine macroinvertebrate response to different water system management strategies under future drivers of change. Water system simulation has been used widely in water planning to examine water resource investment portfolios (Borgomeo et al., 2018), investigate river water quality (Bussi et al., 2016), and explore cooperative transboundary management (Wheeler et al., 2018). Yet few studies have used simulation for the purpose presented here. The proposed joint assessment of river health and water resource planning combines aspects of two paradigms that have traditionally remained separate: environmental flow assessment and risk-based water resource planning. The case study application provides a working example of how the environmental impact of strategic water planning can be tested against future scenarios and associated uncertainties, and how regulation can be moderated through the exploration of emerging trade-offs between water supply and environmental degradation.

2. Data and methods

This section presents a simulation-based framework to inform future water system planning (Fig. 1). The workflow is divided into three sections: (i) statistical hydro-ecological model development using historical flow observations and macroinvertebrate indices; (ii) water resource simulation of regulation strategies under historical and uncertain future scenarios; and, (iii) evaluation of simulated water supply system and macroinvertebrate community response to different management strategies throughout the 21st Century. The framework is designed to evaluate regulation strategies against a wide range of uncertain scenarios, and in doing so explore the trade-offs between river health and reliable water supply. The framework is applied to the River Lee catchment in South East England, which is part of the wider Thames Basin and a public water supply source for London.

2.1. Study area

The River Lee is chosen to demonstrate the utility of the modelling framework. The River Lee catchment covers an area of 1385 km^2, overlays limestone (chalk) geology and flows into the River Thames from North East London (NERC CEH Wallingford, 2018). The water utility Thames Water abstracts water directly from the Lee, supplying customers in Hornsey, Coppermills and the wider London

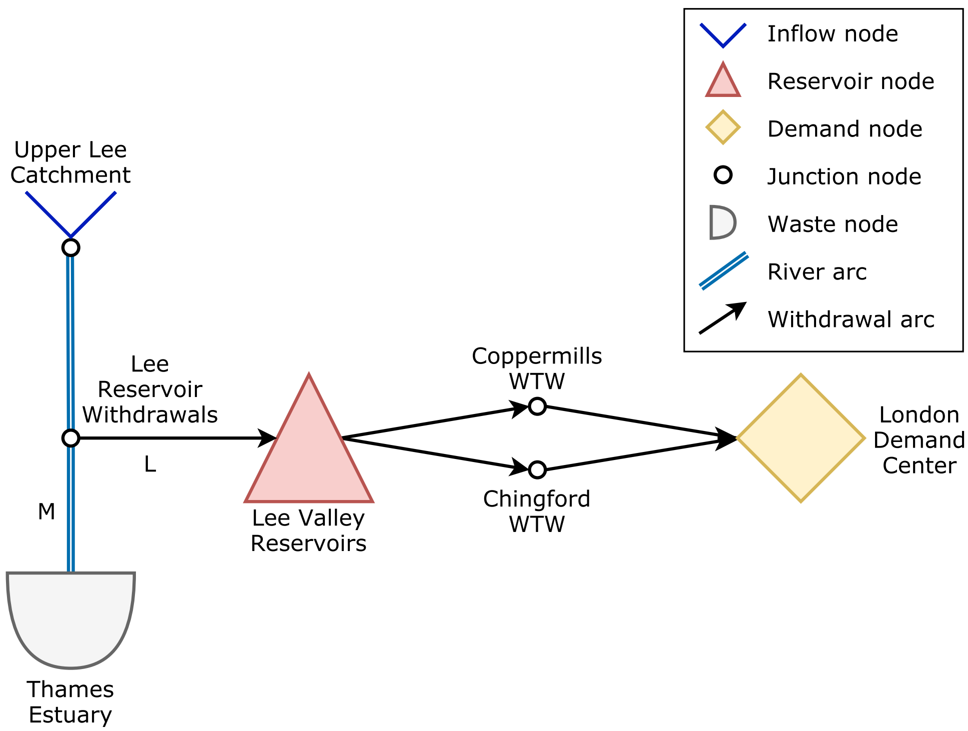

Fig. 2. Water resource system model schematic.

water resource zone. Within the lower Lee Valley, Thames Water operate a sequence of offline raw water storage reservoirs that are principally fed by withdrawals from the Lee. Hydrology along the lower river reach is influenced by surface water withdrawals and discharges from sewage treatment works adjacent to the Lee reservoirs (Mulder et al., 2018).

As part of a national initiative to improve environmental conditions along rivers, the English Environment Agency requires water companies to reduce surface water withdrawals (where feasible) and improve efforts to increase flows in rivers (Environment Agency, 2019a; Thames Water, 2019). Reductions in surface water withdrawals are often fixed in time and defined according to what would be an acceptable level of withdrawal under historical trends. The framework presented here enables simulation of withdrawal licence reduction schemes and flow regulation policies against future climate and demand scenarios, whilst simultaneously evaluating the benefit of increased downstream flows on ecosystem health.

2.2. System model

Fig. 2 presents a simplified schematic of the Lee Valley water system to be modelled. The system is represented by a series of nodes and arcs in the network flow model, WATHNET-5 (Kuczera, 1992). This model has previously been used to simulate long term water resource planning portfolios in the Thames Basin against climate change uncertainty (Borgomeo et al., 2018; Hall et al., 2019). Within WATHNET-5, arcs represent flow pathways (rivers and pipes) that connect inflow, groundwater, reservoir, demand and waste nodes. Flow arcs are assigned individual costs, which prioritise allocation of flow through an arc. Environmental flow arcs are given a negative cost to ensure that the minimum required flow (MRF) is met. In the Lee Valley system model, the current MRF for Arc M is set at 45 Ml/d, based on regulatory requirements for that reach.

In this study, the Lee water supply network was nested within a larger model of the Thames water system. This approach provides more accurate boundary conditions for the individual water network (Dobson et al., 2019), ensuring that water supply allocation within the Lee Valley represents real life management of the Thames system and the interconnected nature of the London water supply grid. Note that multiple inflow and demand nodes in the Thames system model were not represented in Fig. 2. The larger system model contains nine demand nodes, twelve surface water nodes, and seven groundwater nodes. Within the system model, the Lee Valley reservoirs were aggregated into one large reservoir node and were able to directly pump withdrawals from the river. The demand (London Demand Centre) and waste node (Thames Estuary) acted as sinks in the network. The London Demand Centre represented demand of water users in the London water resource zone.

2.2.1. Model inputs

Flows were input into the system model via inflow nodes. This study adopted a coupled climatological-hydrological modelling framework to generate flows for the Lee catchment and other inflow nodes in the larger Thames water system model. Historically observed and emissions-driven precipitation (P) and evapotranspiration (PET) time-series from the CEH GEAR (Tanguy et al., 2019) and Weather@Home (W@H) platform (Guillod et al., 2017), respectively, were used to run the DECIPHeR (Dynamic fluxEs and ConnectIvity for Predictions of HydRology) hydrological model, developed by Coxon et al. (2019).

Weather@Home weather sequences were generated using a Global Circulation Model (HadAM3P) downscaled with the Met Office Regional Climate Model, HadRM3p, and driven with historic (HadISST) and projected (CMIP5) sea surface temperatures (SST) and sea ice. W@H has been shown to perform well over Europe and has been widely used to examine the impact of regional extreme events in Southern England (Borgomeo et al., 2018; Haustein et al., 2016; Mitchell et al., 2016; Schaller et al., 2016). A complete description of the climate modelling process, bias correction, and validation is presented in Guillod et al. (2017, 2018). Modelled W@H P and PET for the Lee and other Thames Basin catchments were simulated for three time periods. In the Baseline period (1975–2004), 100 realisations were generated using different initial atmospheric conditions, and historic SST and sea ice records from HadISST (Rayner et al., 2003; Titchner & Rayner, 2014). In the Near Future period (2020–2049), 100 realisations were generated using 50th percentile SST and sea ice projections (CMIP5, (Taylor et al., 2012)) under Representative Concentration Pathway 8.5 (Meinshausen et al., 2011). 100 realisations were generated for the Far Future period (2070–2099) using 50th percentile SST and sea ice projections under RCP8.5. Because RCP8.5 represents the upper bound of projected global emissions scenarios, it is appropriate for climate impact assessments such as this one which examine the adaptation actions required to combat extreme future conditions.

The DECIPHeR modelling framework consists of sub-catchment-based hydrological response units (HRUs) that group hydrologically similar areas according to landscape attributes and spatial variability of climatic inputs. Previous work has shown that DECIPHeR achieves good model performance across 1366 flow locations in the UK when evaluated against historically observed flows, with 92% of simulations using 10,000 model parameter sets achieving a Nash-Sutcliffe efficiency score greater than zero (Coxon et al., 2019). The best DECIPHeR parameter sets, according to NSE and logNSE scores, were identified for 338 catchments in England and Wales by Dobson et al. (2020) in their analysis of 21st Century droughts. Following the same hydrological modelling framework outlined by Dobson et al. (2020), this study used the best DECIPHeR parameter sets for catchments in the Thames Basin to simulate hydrometeorological flow conditions at a 5 km resolution. Supplementary Information S1 lists the NSE and logNSE of the calibrated historic DECIPHeR flows for the Thames at Teddington (NRFA station 39001) and Lee at Feildes Weir (NRFA station 38001). The water system model (Fig. 2) used DECIPHeR flow sequences for the CEH GEAR historic period (1962–2015), and flow sequences for the W@H Baseline, Near Future and Far Future periods. Plots of the empirical cumulative distribution functions (ecdfs) for simulated flows and corresponding flow statistics for the Upper Lee catchment are presented in Supplementary Information S2. 9000 years of W@H modelled daily flows were available for each inflow node in the system model. Groundwater inflows were set at the licenced withdrawal limit, defined by the Environment Agency (Environment Agency, 2013).

Historical demand was estimated using dry year annual average distribution input at water resource zone level and annual demand profiles, and paired with the historic CEH GEAR-DECIPHeR flow scenario. Ten scenarios of future municipal water demand were estimated using dry year annual average distribution input and demand profiles, and scaled according to Thames Water water resource planning tables (Environment Agency, 2019b; Thames Water, 2019). Each future demand scenario was coupled with the 100 Baseline, Near Future and Far Future W@H-DECIPHeR flow scenarios, to create a library of 3000 scenarios (total of 90,000 simulation years). WATHNET-5 is used to simulate the water system under the historical conditions and 3000 W@H climate and demand scenarios. Simulation output can include, but is not limited to, demand deficits, river flows, minimum required flow violations, and frequency of water restrictions imposed on customers. This study used simulated daily flow volume along Arc M and simulated daily withdrawals along Arc L (Fig. 2).

2.2.2. Water withdrawal strategies

Water is abstracted from the river at the Lee Reservoir Withdrawals point along Arc L in Fig. 2. A 'no change' system model was first run under the historic flow and water demand scenario using the current daily abstraction licence of 1200 Ml/d (Environment Agency, 2013). The simulated water withdrawals over the historic period (1962–2015) were used to identify water withdrawal strategies to be simulated under the future flow and demand scenarios (Table 1). The strategies examined introduce proportional reductions to the simulated daily water withdrawals over the historic period. The system model was also used to explore the impact of altered downstream minimum flow requirements on river health, by simulating regulation policies with different MRF limits along Arc M. The existing MRF below the Lee Reservoirs (45Ml/d) is currently set at the 95th percentile (Q95) of the historical (1900–2000) daily mean flows recorded at NRFA gauging station 38001, located above the reservoir withdrawals point (NERC CEH Wallingford, 2018). The MRF policies simulated here were set at historical percentiles of the same daily flow record (Table 1).

2.3. Hydro-ecological model

Multi-level linear regression modelling was used to examine the impact of future changes in flow on macroinvertebrate ecology within the Lee catchment. The use of multi-level models to analyse hydro-ecological relationships are widespread within the literature (dos Reis Oliveira et al., 2020; Klaar et al., 2014; Mellado-Díaz et al., 2019; Murdoch et al., 2020); popular as a consequence of the partially pooled analysis used and ability to build regression relationships using multi-site data. Multi-level linear modelling was well suited for this case study as macroinvertebrate observations are sparse and inconsistently recorded throughout the catchment, particularly below the reservoir withdrawal point. Here, the hydro-ecological model was built using historical antecedent flow conditions and macroinvertebrate community composition observations across several sites throughout the Lee catchment (Fig. 3).

2.3.1. Macroinvertebrate community composition

Macroinvertebrate community composition data were extracted from the Environment Agency BIOSYS dataset (Environment Agency, 2020). The dataset contains biannual observations collected from standardized monitoring of river sites across England and Wales, and has been used widely in hydro-ecological assessments (Clews & Ormerod, 2009; Dunbar et al., 2010a; 2010b;; Mathers et al., 2016). A list of the taxon recorded in the Lee catchment are provided in Supplementary Information S3. Several standard biomonitoring indices of ecological and hydrological quality were derived from BIOSYS samples, including BMWP, NTAXA, ASPT, LIFE, PSI and EPT. Because this framework focused on the impact of future flow regime on river health, we used LIFE scores as a proxy for river health; an index developed by Extence et al. (1999) to link riverine benthic macroinvertebrate community to prevailing flow regime. In general, low LIFE scores are observed during periods of reduced discharge, whilst higher LIFE scores indicate faster flow velocities with clean substrata (Dunbar et al., 2010a; 2010b). Moreover, for chalk and limestone streams LIFE scores have been shown to be closely related to antecedent summer low flows.

11 MI sampling sites were selected for the analysis (Fig. 3), with 125 summer LIFE score observations (April-September) from 1990 to 2018 used in development of the hydro-ecological models. The set of sampling sites used are listed in Supplementary Information S4. The choice to examine the relationship between antecedent flow and seasonal macroinvertebrate response is consistent with other studies in the literature (Monk et al., 2006; Visser et al., 2019). However, future work could use the proposed framework to explore the impact of climate change, and the role of water-use regulation, on winter LIFE scores (October-March).

Table 1
Regulation strategies to be simulated under future ensemble.

Strategy Code	Withdrawal licence (set at percentile of historical simulated daily water withdrawals along Arc L)	MRF limit (set at percentile of historical daily flow at NRFA station 38001, 1900–2000)
S.a	Q0 (1200Ml/d, current licence)	Q100 (0Ml/d)
S.b	Q0 (1200Ml/d, current licence)	Q98 (24Ml/d)
S.c	Q0 (1200Ml/d, current licence)	Q95 (45Ml/d, current MRF)
S.d	Q0 (1200Ml/d, current licence)	Q90 (68Ml/d)
S.e	Q0 (1200Ml/d, current licence)	Q85 (82Ml/d)
S.c.1	Q10 (TBC in simulation)	Q95 (45Ml/d, current MRF)
S c.2	Q20 (TBC in simulation)	Q95 (45Ml/d, current MRF)
S c.3	Q30 (TBC in simulation)	Q95 (45Ml/d, current MRF)

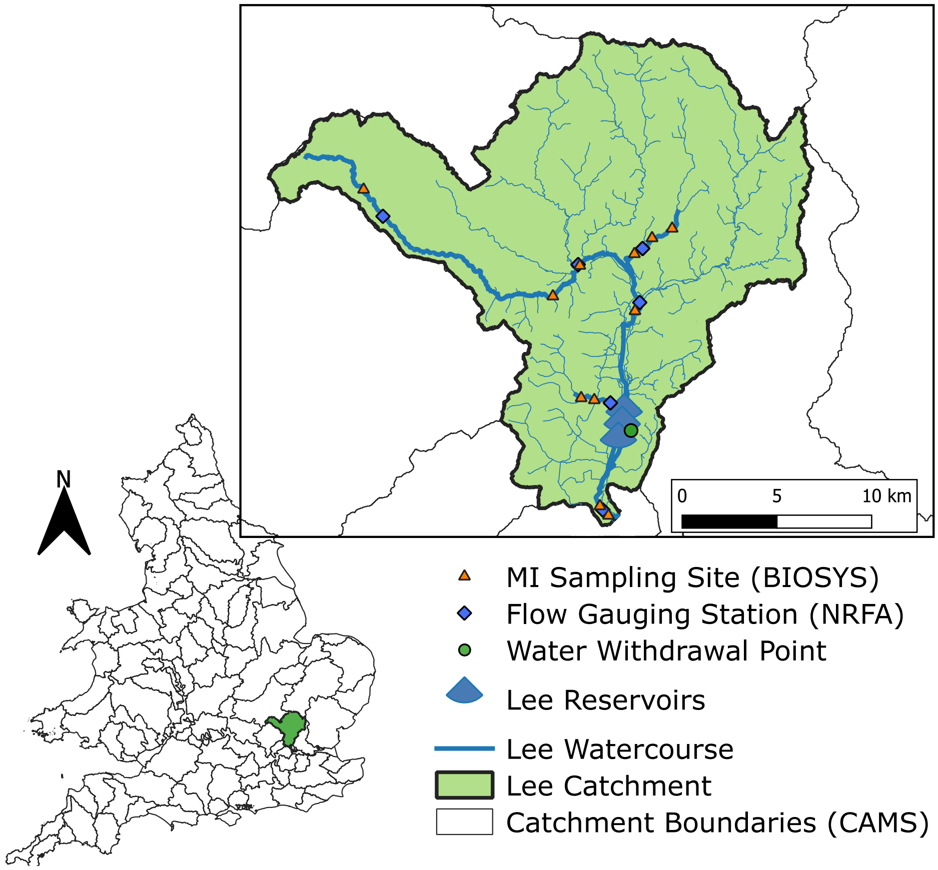

Fig. 3. Study site. Markers indicate locations of National River Flow Archive (NRFA) gauging stations, macroinvertebrate (MI) BIOSYS sampling sites, Lee reservoirs, and Lee reservoir withdrawals point. The Lee watercourse and Catchment Abstraction Management Strategy (CAMS; Environment Agency, 2014) boundaries are also shown.

2.3.2. Flow predictors

Each biomonitoring site was paired with the nearest flow gauging station (Fig. 3; Supplementary Information S5). Mean daily flows from the National River Flow Archive (NERC CEH Wallingford, 2018) were used to calculate antecedent seasonal hydrological indicators (HI) for each macroinvertebrate sample. The indicators considered were ecologically relevant and represented different facets of the flow regime, including extreme flows, low flows, high flows, and rates of change in flow (Richter et al., 1996). Consistent with other studies that evaluate macroinvertebrate response to antecedent flow conditions (Chadd et al. (2017); Dunbar et al. (2010a (2010b); Extence et al. (1999)), this study divided each hydrological year into two periods: summer flows (April-September) and winter flows (October-March). 30 hydrological indicators in total were considered, with 15 HIs for each seasonal period (Supplementary Information S6).

All hydrological indicators considered are unitless, which is necessary when building multi-level linear regression models using data observed across multiple sampling sites (Dunbar et al., 2010a; 2010b). The HIs were categorised into two groups. The first group defined HIs by flow quantiles, and were standardized relative to the long-term observations at individual gauging station locations. The standardized flow statistic, z_{im} in period i at site m, was calculated $z_{im} = \frac{(x_{im} - \mu_m)}{\sigma_m}$, where x_{im} represents the observed flow statistic in period i at site m, μ_m the long-term mean of the flow statistic at site m, and σ_m the standard deviation in the observed flow statistic record at site m. Negative z-statistics indicated below average quantile values relative to the historic record; positive z-statistics represented above average values. The second group of hydrological indicators were calculated as the proportion of days within a season that satisfy set criteria, such as the proportion of days when daily flow is less than historical Q90, or the proportion of days when flow is increasing (i.e. positive reversals). These HIs did not need to be standardized because the HI was represented as a number between 0 and 1. Here, 0 indicated no days in the season when the flow criteria are satisfied, and 1 indicated all days in the season satisfy the criteria.

2.3.3. Statistical methodology

This study followed a modified version of the statistical methodology presented by Dunbar et al. (2010a, 2010b), who used sampling site location as a grouping variable in the multi-level linear regression model. The multi-level model consisted of fixed and random effects; fixed effects determined model intercept and slope, and explained the overall response of the model across multiple sampling sites. In the multi-level model, individual hydrological indicators from the same gauging station represented the 'within site' level of the model and were expressed as fixed effects. In line with Dunbar et al. (2010a, 2010b), random effects explained variation around the overall LIFE score response. The Lee hydro-ecological model developed here was classified as multi-level because random effects existed at two levels: among sampling sites and within sampling sites.

Multi-level hydro-ecological models using different combinations of HI were investigated following the flowchart presented in Fig. 4. In developing the model, we tested the hypothesis that antecedent flow in the preceding two seasons before a macroinvertebrate sample influences macroinvertebrate health. This is consistent with other studies that have tested the effect of seasonal antecedent flow

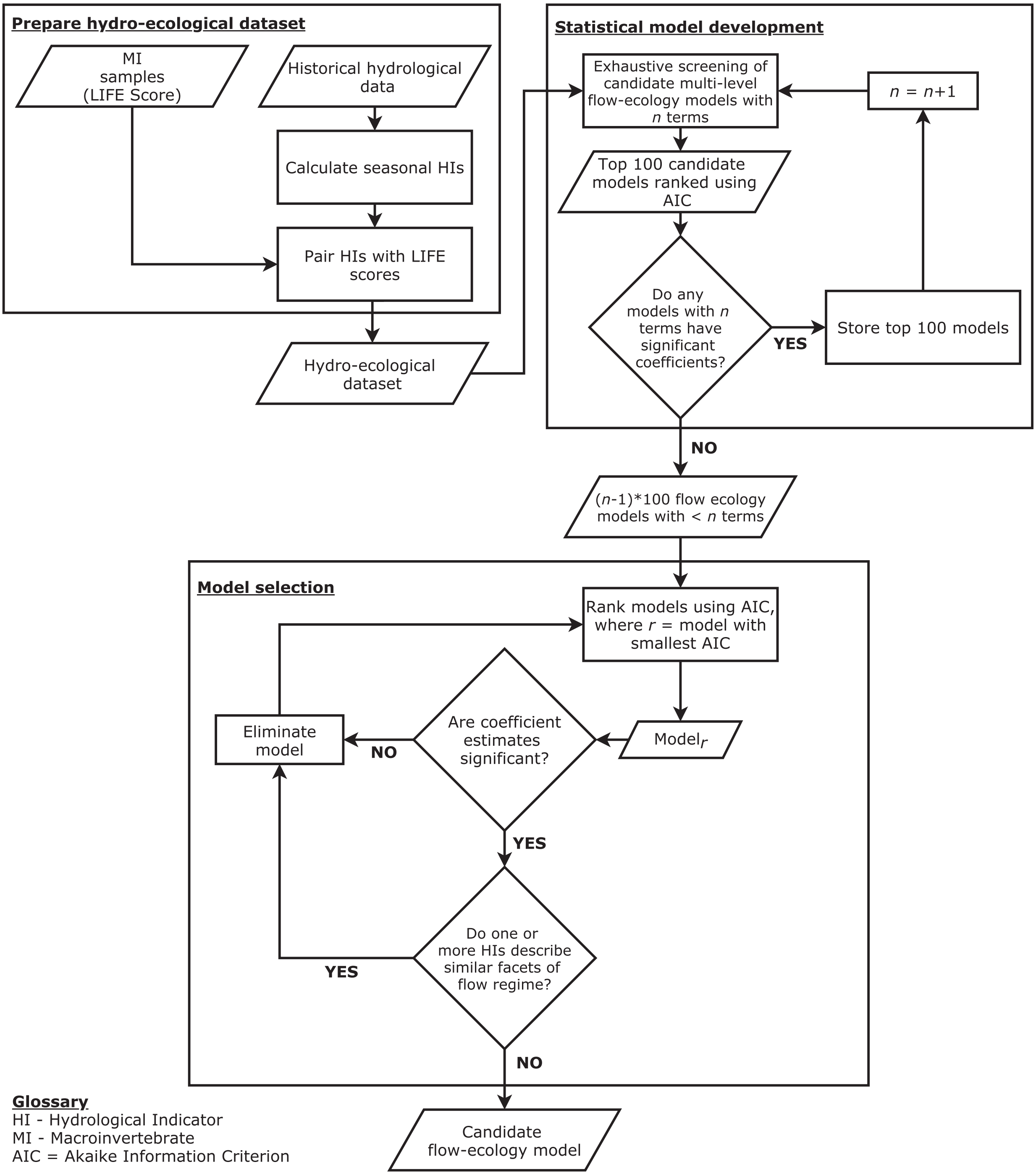

Fig. 4. Process of selecting candidate multi-level linear hydro-ecological model.

conditions, including Chadd et al. (2017), Worrall et al. (2014), Dunbar et al. (2010a), and Dunbar et al. (2010b) The R packages *Glmulti* (Calcagno, 2013) and *lme4* (Bates et al., 2015) were used to fit multi-level models with HIs from the winter and summer season preceding a summer macroinvertebrate sample. *Glmulti* exhaustively screened candidate models, examining all possible combinations of HIs for a given number of model terms. Models were first fit with one term, increasing in complexity with each screening. The models from each screening were ranked according to Akaike Information Criterion (AIC) and the top 100 from each screening were used in the next stage of model development. Candidate model screening was terminated when all estimated coefficients for the multi-level models of a given screening were non-significant (*P-value* > 0.05). Next, the top 100 models from each screening stage were pooled and ranked again using AIC. Starting from the best model, the models were evaluated sequentially. A model was rejected if it contained (i) non-significant fixed effect parameter coefficient estimates, or (ii) more than one HI that described similar facets of the flow regime in the same season (see Supplementary Information S6). The first model to satisfy the selection criteria was used for macroinvertebrate index simulation.

2.4. Macroinvertebrate index simulation

Upon selecting suitable HIs for the candidate hydro-ecological model, the model was used to simulate LIFE scores along Arc M in the historical, Baseline, Near Future and Far Future periods. Here, Arc M was treated as a new sampling site. Because the hydro-ecological model was built with a partially pooled analysis using data from multiple sites throughout the Lee catchment, the regression relationship derived for Arc M was skewed towards the overall relationship for all sampling sites used in the study. This 'borrowed strength' is advantageous in predicting macroinvertebrate response for sites with scarce data (Dunbar et al., 2010a; 2010b;; Gelman & Hill, 2007).

Hydrological indicators for Arc M were calculated using the same procedure described in Section 2.3.2. The system model was first run under a 'do nothing' strategy (Strategy S.c) using the historical scenario to establish historical hydrological indicators for Arc M. For hydrological indicators defined by flow quantiles, the mean μ_a and standard deviation σ_a of the explanatory flow quantile were derived from the historical simulation and used to standardize the equivalent flow statistic in future simulations. For example, in simulations under future conditions the flow quantile x_{ia}, at site a (Arc M), was transformed into the standardized hydrological indicator, z_{ia}, in period i, according to $z_{ia} = \frac{(x_{ia} - \mu_a)}{\sigma_a}$. For HIs that represented the proportion of days in a season that satisfied set criteria, the criteria were again calculated using seasonal flow statistics along Arc M from the historical simulation. For example, the proportion of days in a summer season when flow is less than historic summer Q90 was calculated using the long-term summer Q90 from the historical simulation. The calculation can be written: $p_{ia} = \frac{\sum_{t=1}^{n} 1_{f_{ta} < x_{ha}^{v}}(f_t)}{n}$, where p_{ia} is the proportion of days at site a in period i with n days, when flow f_t is less than the flow statistic x_{ha}^{v}, where x is derived from the historical simulation h at site a in season v (where season v can be winter or summer). The workflow was designed to ensure that all future simulated HIs were scaled relative to historic conditions observed under simulations of the current water withdrawal strategy and water supply infrastructure.

To account for uncertainty when predicting LIFE score, we estimated the distribution of residuals in the historically observed data using a non-parametric kernel distribution estimator. For the candidate multi-level linear regression model, we calculated the non-parametric estimation of the probability density function (pdf) of the model residuals. A randomised predictor of LIFE score was then generated for each simulated observation by sampling from the estimated distribution. The sample was then added to the LIFE score calculated from the multi-level linear regression model using the same observation period. The final predicted LIFE scores represented the statistical relationship between antecedent flow conditions and macroinvertebrate community response, and reflected the residual uncertainty in macroinvertebrate community response. The workflow for simulating future LIFE scores can be summarised:

(i) Estimate coefficients, $\widehat{\beta}_0$ and $\widehat{\beta}_1$ to $\widehat{\beta}_w$ for candidate multi-level linear regression model:

$$LIFE_{im} = \beta_0 + \beta_1 D_{im}^1 + \beta_2 D_{im}^2 + \ldots + \beta_k D_{im}^k + b_{0m} + \varepsilon_{im}$$

where $LIFE_{im}$ represents the LIFE score observation in period i at level (site) m, β_0 denotes the intercept term, β_1 to β_k are the hydrological indicator coefficients for D_{im}^1 to D_{im}^k, which signify the hydrological indicator in period i for level m, b_{0m} represents the random effect for level m, and ε_{im} the error term for observation in period i at level m.

(ii) Calculate the estimated residual, $\widehat{\varepsilon}_{im}$, for each LIFE observation:

$$\widehat{\varepsilon}_{im} = LIFE_{im} - \widehat{\beta}_0 - \widehat{\beta}_1 D_{im}^1 - \widehat{\beta}_2 D_{im}^2 - \ldots - \widehat{\beta}_k D_{im}^k - \widehat{b}_{0m}$$

(iii) Fit non-parametric distribution Ω to estimated residuals $\left\{\widehat{\varepsilon}_{im}\right\}_{i=1,\cdots,R,m=1,\cdots,J}$

(iv) Simulate LIFE score at site a in period i:

$$LIFE_{ia} = \widehat{\beta}_0 + \widehat{\beta}_1 D_{ia}^1 + \widehat{\beta}_2 D_{ia}^2 + \ldots + \widehat{\beta}_k D_{ia}^k + b_{0a} + \varepsilon_{ta}$$

where ε_{ta} Ω.

3. Results

3.1. Hydro-ecological model fit and forecast skill

Multi-level hydro-ecological models were built using paired historical flow and macroinvertebrate observations. The final set of candidate hydro-ecological models are listed in Supplementary Information S7 and are ranked according to AIC. Ten models in the top 20 consisted of three HIs, each reflecting facets of the flow regime in the summer and winter season prior to MI sampling. The most common summer HIs selected for the multi-level model included standardized Q90 ($Q90z_S$) or Q80 ($Q80z_S$), and/or measures of the proportion of days in which flow exceeds extreme historical flow percentiles ($MTQ10_S$ or $LTQ90_S$). The most frequently selected winter HIs describe average flow conditions ($MTQ50_W$ or $LTQ50_W$) or mild flow events ($MTQ30_W$ or $LTQ70_W$). The pattern of HI selection in the final stage of model development indicates that LIFE scores in the Lee Valley were susceptible to changes in extreme flow conditions in summer, and flow stability relative to the mean conditions in winter. Interestingly, HIs representing rates of change in flow (positive/ negative reversals) did not feature in the final set of hydro-ecological models. This suggests that HIs representing the magnitude and extent of the flow regime were more relevant for evaluations of river health in the Lee catchment (although this is not necessarily true for all catchments).

The model selected for future simulations consisted of hydrological indicators corresponding to: (i) the proportion of days in the summer preceding a LIFE score observation with flow greater than the historical Q10 ($MTQ10_S$), (ii) the standardized summer Q90 ($Q90z_S$) in the summer preceding a LIFE score observation, and (iii) the proportion of days in the winter immediately preceding a LIFE score observation with flow less than the historical Q50 ($LTQ50_W$). Table 2 lists the parameters of the multi-level hydro-ecological model, including the parameter coefficients and corresponding *P-values*. Fig. 5a highlights the timing of seasonal HI observations for the candidate model. The parameter estimate for $Q90z_S$ suggests that above average summer low flows positively influence LIFE scores, whilst below average low flows are harmful for river health. In contrast, a high proportion of days in summer when flow exceeds historic Q10 will negatively influence LIFE scores. Together, the parameter estimates for $MTQ10_S$ and $Q90z_S$ suggest that river health in the Lee may be vulnerable to extreme low and high flow events in the summer preceding a MI sample. The negative parameter estimate for $LTQ50_W$ suggests that average winter conditions have greater control over LIFE scores than extreme winter flows, with an increase in the proportion of days below the historical winter Q50 resulting in lower LIFE scores. Fig. 5d, e and f confirm the interaction of $MTQ10_S$, $Q90z_S$ and $LTQ50_W$ with summer river health, illustrating graphically the mean site and individual site relationships between HIs and LIFE score.

To account for variability in the fitted LIFE response around the model regression line, we used the kernel density estimator to estimate the pdf of the model residuals. Fig. 5b plots the model residuals versus the fitted LIFE values, which are used to estimate the pdf presented in Fig. 5c. When simulating future LIFE scores, a randomised predictor of LIFE score was sampled from this pdf and added to the predicted LIFE score from the multi-level model.

3.2. Macroinvertebrate simulation

This section presents simulated summer LIFE scores for the stretch of river below the Lee reservoir withdrawal point (Arc M) for the different regulation strategies (Table 1) when simulated against the historic scenario (1962–2015), and Baseline (1975–2004), Near Future (2020–2049), and Far Future (2070–2099) ensembles. The results explore the difference between simulated LIFE scores under the strategies, identifying policies that help to maintain river health in the Lee Valley under increasing climate and demand side pressures. The results primarily focus on strategy performance in the Near and Far Future simulations, as these simulations used RCP-driven flow scenarios. However, simulation results from the Baseline ensemble are also presented for reference.

Fig. 6a presents the kernel density estimated pdf of simulated summer LIFE scores under Strategy S.c. This strategy represents the current system state without changes to regulatory policies. The historic pdf is represented by the orange line, Baseline by green, Near Future by blue and Far Future by red. Simulations of the W@H ensembles result in a shift in mean LIFE score distribution towards lower LIFE scores, with lower mean and minimum simulated LIFE scores relative to the historic simulation (Supplementary Information S8). This is attributed to the increased demand pressures in the three ensembles, and decreased water availability in the Near and Far Future ensembles. The range of simulated LIFE scores increased in both Near and Far Future simulations, with higher maximum

Table 2
Parameters of candidate hydro-ecological model.

	Parameter	SE	P-value*
Fixed effects			
Intercept	6.604	0.196	<0.001
$MTQ10_S$	−0.967	0.367	0.009
$Q90z_S$	0.137	0.044	0.002
$LTQ50_W$	−0.263	0.112	0.021
Random effects+			
Intercept	0.570		
Residual	0.294		

*Based on T-tests, +Expressed in LIFE score units.

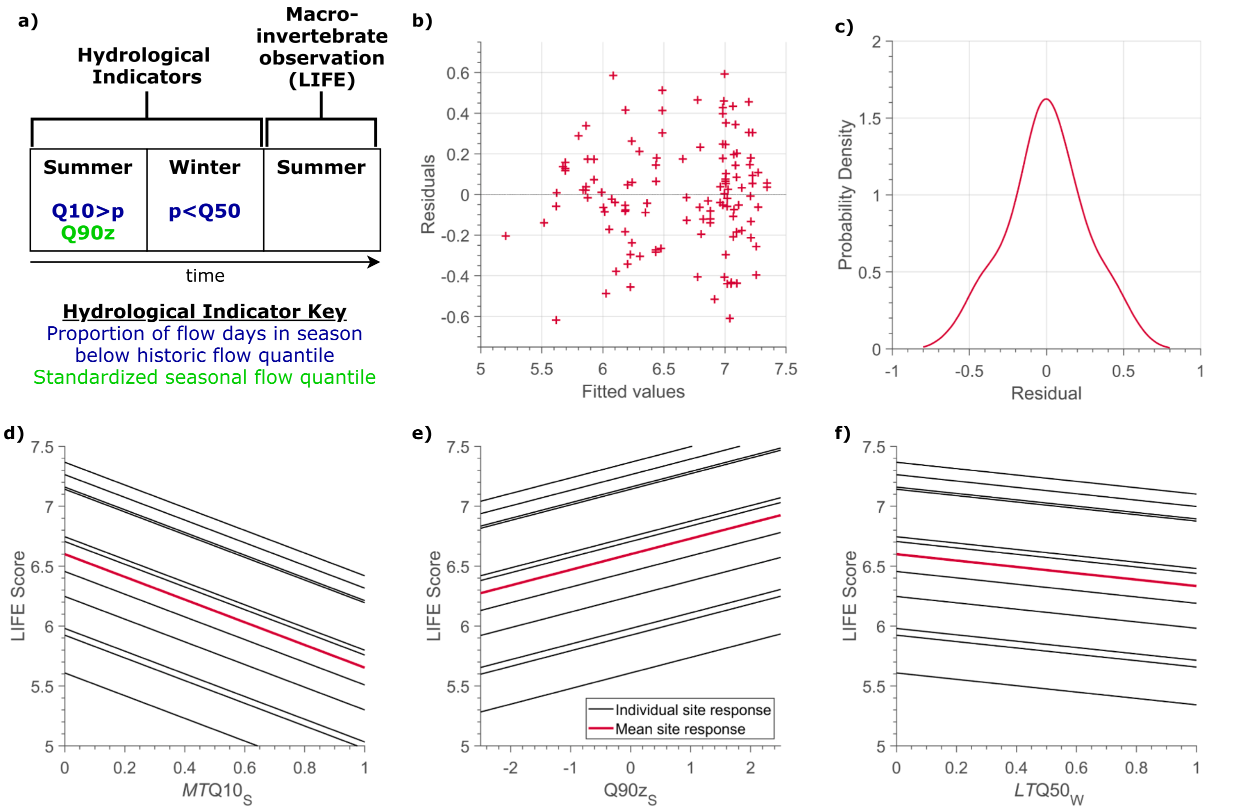

Fig. 5. Features of the candidate hydro-ecological model. **5a** presents timeline of model terms and MI sampling. **5b** plots the model residuals versus fitted LIFE scores. **5c** shows the probability density curve of model residuals derived from kernel density estimator. **5d** illustrates Lee hydro-ecological model using antecedent $MTQ10_S$ as a predictor, with $Q90z_S$ and $LTQ50_W$ held constant. **5e** illustrates Lee hydro-ecological model using antecedent $Q90z_S$ as a predictor, with $MTQ10_S$ and $LTQ50_W$ held constant. **5f** illustrates Lee hydro-ecological model using antecedent $LTQ50_W$ as a predictor, with $MTQ10_S$ and $Q90z_S$ held constant. In Fig. 5**d to 5f** the red line indicates overall relationship at the mean sampling site; black lines indicate individual site relationships between HI and LIFE score.

simulated LIFE scores estimated for the future ensembles compared to the maximum score simulated under historic conditions. Fig. 6b, c and d illustrate the shift in simulated LIFE scores in the three future ensembles away from the scores simulated under historic conditions. The plot presents ecdfs of the range and mean simulated LIFE scores, with the shaded areas representing the range of simulated LIFE scores observed between individual scenarios in the ensembles. Fig. 6b shows that LIFE scores simulated under historic conditions fall within the range of scores simulated under the Baseline ensemble. Fig. 6c and d indicate that the range of simulated LIFE scores will narrow and shift towards lower scores throughout the 21st Century. The overall shape of the cdfs and pdfs imply that without adaptation, mean LIFE scores will decrease over time, with higher scores becoming increasingly unlikely by the 2070s.

The change in distribution of simulated LIFE scores over time is attributed to lower simulated $Q90z_S$ and higher simulated $LTQ50_W$ values along Arc M in the Near and Far Future ensembles, relative to the historic scenario. Ecdf plots of the hydrological indicators in the Near and Far Future periods are presented in Supplementary Information S9. Looking at $Q90z_S$, a distinct decrease is observed over time between the historic, Near, and Far Future periods, caused by an increase in the number of days in the summer season when flow along Arc M equals the minimum flow requirement. In the Far Future ensemble, summer flows are dominated by the MRF, resulting in over 80% of days in the simulation when flows equal Strategy S.c's MRF of 45Ml/d. The Near and Far Future ensembles also experienced an increase in the proportion of days in winter with flow less than the historic Q50 ($LTQ50_W$), suggesting that medium to high winter flow volumes in the Lee river will decrease throughout the 21st Century.

Fig. 7 illustrates the trade-off between river health and water supply under increased demand and supply side pressures in the Far Future ensemble. The surface plot shows the average simulated LIFE score achieved for a given volume of total seasonal water withdrawals (abs, Ml) under Strategy S.c. Surface colour represents the simulated LIFE score calculated for the summer following one year (summer + winter) of withdrawals, with blue shades indicating high LIFE scores and red representing low scores. Where multiple LIFE scores are achieved under the same combination of summer and winter abstractions, the average LIFE score is plotted. The highest LIFE scores (>6.5) are principally observed following years with low seasonal water withdrawals, with the exception of the rightmost part of the graph. This anomaly arises from LIFE scores simulated following years with higher than average winter flows (i.e. a low $LTQ50_W$ value) and consistently high water withdrawals. The lowest LIFE scores (<6.5) were detected following years with high summer total abstractions. This pattern emerged as a consequence of increased pressures in the future simulations. Under high water

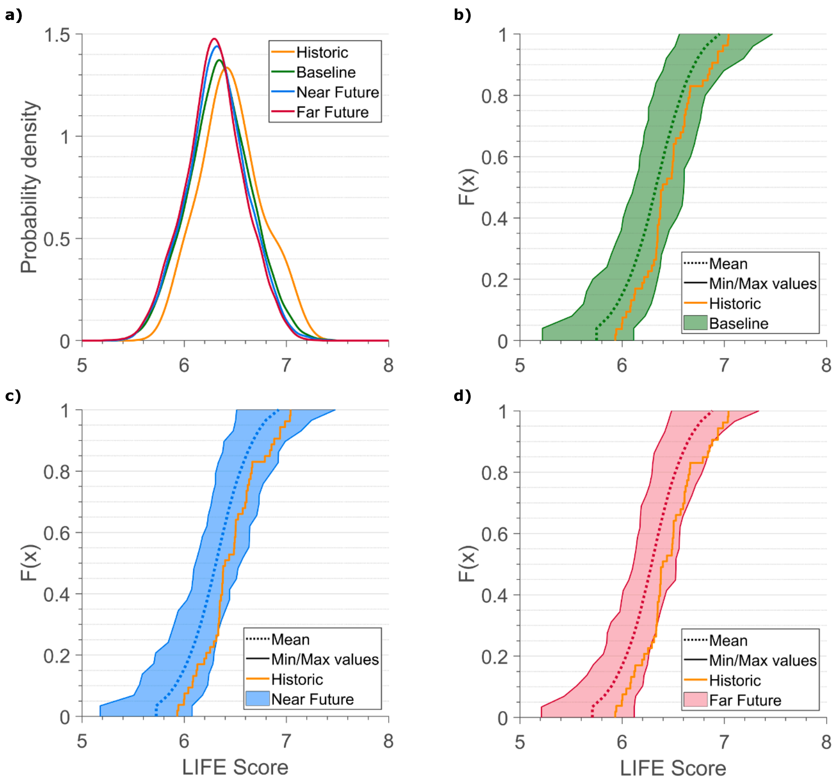

Fig. 6. Distribution of simulated LIFE scores under Strategy S.c. **6a** plots Kernel density estimated pdf of simulated LIFE scores from simulations of Strategy S.c under the historic scenario, and Baseline, Near Future and Far Future ensembles. **6b, 6c** and **6d** plot the empirical cumulative distribution of individual scenarios of simulated LIFE scores from simulations of Strategy S.c under the Baseline, Near Future and Far Future conditions, respectively. The solid lines show the range (minimum/ maximum) of simulated LIFE scores in the W@H ensemble; dashed lines show the mean simulated LIFE scores in the W@H ensembles; orange line represents the empirical cdf for the historic simulated LIFE scores.

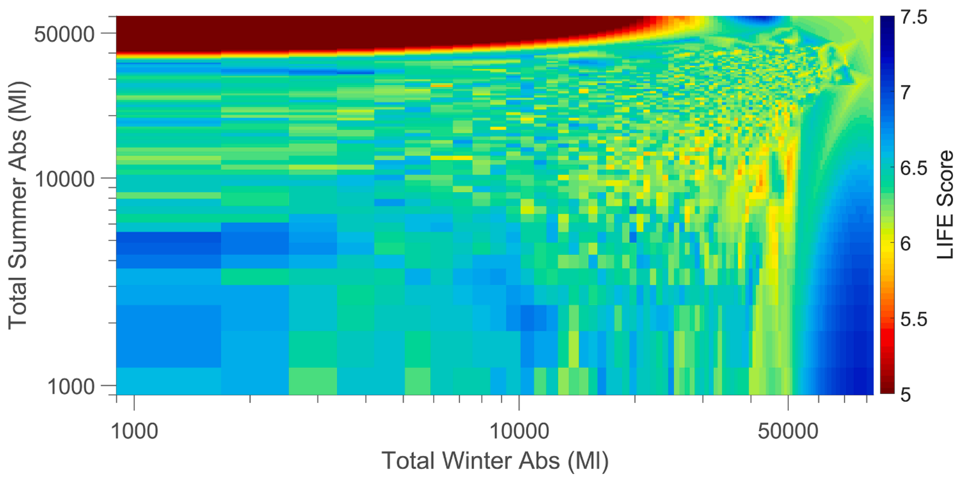

Fig. 7. Surface plot of simulated total winter and summer withdrawals (abs, Ml) under Strategy S.c in the Far Future ensemble. Surface colour represents the simulated average LIFE score calculated for the summer following the previous year's seasonal water withdrawals.

stress the size of daily water withdrawals increased, with abstractions taking as much water from the river as the withdrawal policy and MRF regulation allowed. Given that the Near and Far Future ensembles contained scenarios with increased demand and supply side pressures, flow along Arc M in future simulations was at the lowest permissible level for longer durations relative to the historic simulation. This impacted the HI values used to simulate LIFE scores in the hydro-ecological model, thus producing lower simulated LIFE scores.

A decrease in years with low total winter abstractions also emerged between the historic, Near, and Far Future ensembles (not plotted), attributed to a greater requirement for winter withdrawals in the Far Future following dry summer conditions. Lower summer flows deplete reservoir levels, resulting in a greater need for larger and more frequent winter abstractions. This had a noticeable impact on $LTQ50_W$, as the proportion of days when flow along Arc M was less than historical Q50 increased as winter abstractions grew in frequency and magnitude. This resulted in lower simulated LIFE scores relative to the earlier ensembles as winter flow conditions along Arc M became drier.

Table 3 presents statistics of simulated LIFE scores achieved under the different regulation strategies when simulated against the Near and Far Future ensembles. LIFE score statistics from the simulation of Strategy S.c under the historic scenario are also listed for comparison. Decreases to daily withdrawal licence in S.c.1, S.c.2 and S.c.3 were defined according to percentiles of the simulated daily withdrawal distribution of Strategy S.c when run under the historic scenario (see Supplementary Information S10 for more information). The purpose of Table 3 is to summarise the success of regulation schemes in mitigating the impact of climate change and demand side pressures on LIFE scores in the 21st Century.

Table 3 shows that strategies with decreased MRFs relative to the current limit resulted in a shift in mean simulated LIFE score towards lower scores. The lowest scores were achieved under Strategy S.a, with a mean simulated LIFE score of 6.28 in the Near Future, and 6.25 in the Far Future. This was unsurprising given lowered minimum flow requirements permit flows along Arc M to fall closer to zero. Whilst Strategy S.a would not be considered environmentally acceptable in real world policy planning, it does provide an estimate of the consequence of increased zero flow days may have on LIFE scores. The simulated impact of flow intermittence was somewhat dampened in this case study example because the hydro-ecological model was built using historical flow records with few zero flow days. However, other studies have shown that increased flow intermittence and drying states can have controlling influence aquatic, semi-aquatic and terrestrial invertebrate communities (England et al., 2019).

Strategies that increased the MRF along Arc M relative to S.c resulted in a shift in simulated LIFE score distribution towards higher scores. The strategy with the highest MRF, S.e, achieved the highest mean simulated LIFE scores of all strategies simulated, producing a mean of 6.36 across the Near Future ensemble, and 6.33 across the Far Future. By raising the MRF, S.e limited the volume of water permitted for withdrawal into the Lee Reservoirs. Whilst this change did not impact high flow events in summer ($MTQ10_S$, see Supplementary Information S8), the increased MRF did ensure that flow along Arc M was higher during low flow periods. This resulted in more positive values of $Q90z_S$, and smaller values of $LTQ50_W$. Results from the simulation of S.e indicate that, for a given summer in the same scenario we may see up to 21.5% improvements in simulated LIFE scores compared to S.c in the Near Future ensemble, and up to 21.3% improvements in the Far Future.

Strategies with decreased daily withdrawal licences (S.c.1, S.c.2 and S.c.3) showed no improvement in mean simulated LIFE score when compared to simulations of Strategy S.c, indicating that an increased MRF is more beneficial to average simulated LIFE scores under the wider ensemble conditions. Surprisingly, mean simulated LIFE score achieved under Strategies S.c.1, S.c.2 and S.c.3 were higher for the Far Future period than the Near Future; a direct consequence of more summer seasons in the Near Future ensemble exhibiting a high proportion of days when flow along Arc M exceeded the historic simulated Q10 ($MTQ10_S$). This increase in summer high flow days was caused by two factors: (i) the Near Future DECIPHeR flow ensemble contained more summer high flow events than the Far Future (see Supplementary Information S2); and, (ii) a higher volume of water was abstracted from the river during summer high flow events in the Far Future to cope with decreased overall water availability, thus reducing the value of $MTQ10_S$ along Arc M compared to equivalent measures observed under Near Future simulations (see Supplementary Information S9).

Consistent with Visser et al. (2019), the results presented in Table 3 reveal a decrease in variance of simulated LIFE scores between the Near and Far Future periods. This is attributed to flows along Arc M becoming more similar throughout the 21st Century; which in turn is a direct consequence of (i) more homogenous simulated inflows for the Lee Catchment under the RCP-driven ensembles, and (ii) an increased requirement for water withdrawals as demand and supply side pressures worsen. The results also reveal a reduced

Table 3
LIFE score statistics achieved under regulation strategies when simulated against historic scenario, and Near Future and Far Future ensembles.

Time period	Strategy	Mean LIFE Score	Variance in LIFE Scores
Historic (1962–2015)	S.c	6.455	0.082
Near Future (2020–2049)	S.a	6.280	0.090
	S.b	6.302	0.090
	S.c	6.322	0.088
	S.d	6.341	0.088
	S.e	6.356	0.087
	S.c.1	6.284	0.077
	S.c.2	6.286	0.077
	S.c.3	6.281	0.077
Far Future (2070–2099)	S.a	6.251	0.085
	S.b	6.275	0.084
	S.c	6.298	0.085
	S.d	6.319	0.083
	S.e	6.333	0.084
	S.c.1	6.295	0.076
	S.c.2	6.295	0.075
	S.c.3	6.295	0.076

variance of simulated LIFE scores under S.c.1, S.c.2 and S.c.3 compared to all other strategies. To compensate for the reduction in daily withdrawal limit of these strategies, larger volumes of water were taken more frequently throughout the year in future simulations. This therefore preserved flow volumes along Arc M equal to the MRF for longer durations of time. This meant that differences in intra-seasonal, inter-annual, and inter-scenario flow volumes along Arc M were lessened, and thus LIFE score variation dampened. This result is reflected in the ecdfs of hydrological indicators along Arc M in Supplementary Information S9, which show reduced ranges of scenario ecdfs across the future ensembles under strategies with decreased withdrawal limits.

Overall, the results indicate that of all the strategies simulated, S.e produced simulated LIFE scores in the future ensembles closest to the distribution derived from simulations using historic conditions. This suggests that S.e will be most beneficial in maintaining river health throughout the 21st Century, helping to mitigate against future pressures arising from increased water demand and decreased supply. By increasing the minimum required flow downstream of the reservoir withdrawal point, water companies will be forced to maintain higher flow levels throughout the year thus preventing over-abstraction during low flow events.

It is important to note that none of the strategies simulated were able to reproduce the mean LIFE scores simulated in the historic period. For this reason, a final investigation was conducted using a new strategy, S.f, which was designed to preserve and prioritise LIFE score into the future. This strategy used the current licence limit and MRF requirements (as with Strategy S.c), but also assigned a high positive cost to the withdrawal arc linking the River Lee and Lee Reservoirs (Arc L). This high cost directly influenced the likelihood of flow through the arc, prioritising flow downstream over water withdrawals in all conditions. Under this strategy, mean total summer water withdrawals in individual scenarios in the Near and Far Future ensembles were on average 99.6% and 99.2% less, respectively, than withdrawals recorded in simulations of Strategy S.c. In winter, the equivalent measure of withdrawals decreased by 99.5% in the Near and 98.8% in the Far Future simulations. Consequently, Strategy S.f successfully maintained the mean simulated LIFE score estimated for the historic period under S.c in the Near Future ensemble (6.479), and resulted in a marginal decrease in mean score in the Far Future ensemble (6.451). Fig. 8 presents the range and mean of simulated LIFE score ecdfs from simulations of Strategy S.f under the Near Future and Far Future ensembles, plotted alongside the ecdf of simulated LIFE scores achieved under Strategy S.c in the historic simulation. The figure further illustrates the success of Strategy S.f in maintaining mean LIFE scores into the future, but indicates that the strategy failed to guarantee robustness to the full range of conditions present in the Near and Far Future ensembles.

Overall, the results suggest that more stringent regulation is required to maintain river health along the lower Lee River in the mid to late 21st Century; an action that will likely come at the expense of maintaining water supply security. In the face of more stringent water withdrawals in the Lee, large infrastructure developments, such as those discussed by Borgomeo et al. (2018) and Murgatroyd & Hall (2020), will be necessary to balance the projected changes to water demand in the face of climate change and avoid over-exploitation of existing surface water supplies.

4. Discussion and conclusions

Recent research has highlighted the importance of consolidating environmental science and water planning when designing riverine management portfolios (Poff, 2018). Management frameworks must recognize uncertainties inherent to long term planning, whilst also assessing trade-offs that emerge between improved water security and ecosystem health (Arthington et al., 2018). The framework and case study example presented here illustrated how this can be achieved, using a simulation driven approach directly linked to empirical indicators of ecological condition. The workflow can be used to test regulation strategies against climate and population driven changes in water demand and supply, offering practical guidance on how to quantify the impact of future changes on

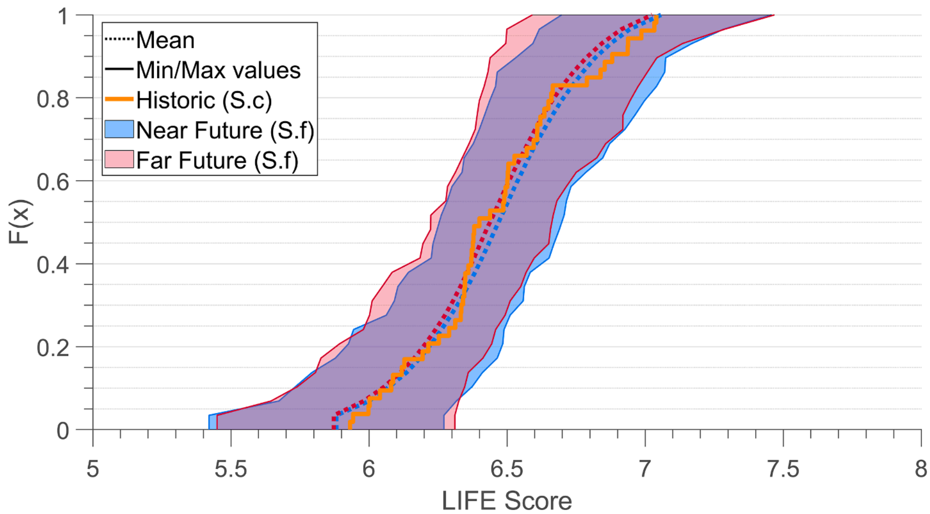

Fig. 8. Empirical cumulative distribution function plot of simulated LIFE scores from simulations of Strategy S.f under Near Future and Far Future ensembles. The solid lines show the range (minimum/ maximum) of simulated LIFE scores in the ensemble; dashed lines show the mean simulated LIFE scores in the ensembles. The orange line represents the empirical cdf for the historic simulated LIFE scores under Strategy S.c.

macroinvertebrate community. In doing so, the framework facilitates effective communication of risk to practitioners and policy makers (Acreman et al., 2014).

The empirically driven multi-level linear modelling used in this study offers a mechanism to incorporate macroinvertebrate response in water resource system simulation. The partially-pooled analysis draws on hydro-ecological relationships at other locations along the river, to: (i) balance generic hydro-ecological relationships within the catchment with local relationships (Klaar et al., 2014), and; (ii) allow the hydro-ecological response to be scaled to broader spatial scales (Stoffels et al., 2018). First, an exhaustive model search was used to identify flow statistics (hydrological indicators) that are most relevant to measure ecological health in the study area. This stage is important for adaptive planning problems, where indicator choice can influence policy success (Giuliani et al., 2015). The proposed search process ensures that the set of selected indicators are: (i) complete, with a combined ability to best represent the critical uncertainties that control macroinvertebrate response; and, (ii) parsimonious, thus helping to avoid increased dimensionality of the planning process by selecting unnecessary indicators (Raso et al., 2019). Upon identifying hydrological indicators to best represent the macroinvertebrate observations, the multi-level model and estimation of residual uncertainty provided the understanding necessary to regulate flow in a way most relevant to ecological response. Moreover, the BIOSYS and NRFA dataset used provided bottom-up information rarely utilized in top-down climate impact assessments (Conway et al., 2019; Westwood et al., 2017). Here, the iterative process guided practical adaptation by combining top-down emissions driven projections of 21st Century flow and population driven water demand with bottom-up site-specific observations of macroinvertebrate health and daily flow data.

The case study application further illustrated the importance of developing a clear understanding of the hydrology in the area being assessed, how it may change into the future, and the extent to which the hydrology is impacted by regulation. Achieving a comprehensive understanding in this way is difficult using only historically observed data, particularly in data sparse areas with limited monitoring of regulatory activity. By adopting simulation based methods, we were able to decipher that, under historic conditions, water withdrawals into the Lee reservoirs are limited by water availability and minimum flow requirements, rather than the daily withdrawal licence. This understanding helped to identify regulation strategies that invoke a change in downstream flow and positively impact river health. Simulation was successfully used to explore the magnitude of regulatory action required to maintain LIFE scores into the future. Results indicated that: (i) under the current regulation policy, mean LIFE scores will decrease into the future; (ii) licence reductions prove ineffective in maintaining LIFE scores under increased demand and supply pressures; and, (iii) changes to minimum required flow constraints downstream of the withdrawal point have the greatest impact on river health. In the example presented here, we conclude that the impact of climate change and increased demand can be lessened only if the maximum daily withdrawal licence is greatly reduced and the MRF below the withdrawal point is increased. In rivers where withdrawal volumes are more frequently limited by regulatory licences, we expect that smaller decreases in licence limits would protect LIFE scores downstream from future impacts of climate change and growing demand.

Whilst scenario-driven assessments are common in the water planning and management literature, they are rarely explored in environmental flow literature. The results presented here further emphasize the necessity to assess river management portfolios against uncertain future scenarios. Assessments of regulatory policies using only historic conditions fail to consider hydro-ecological response under events not present in the observed record. This is especially evident here, as the historic scenario contained fewer low flow events of the same severity and intensity as the future ensembles. As Visser et al. (2019) found, emissions driven changes in hydrology may result in increased probability of extreme hydro-ecological response, thereby increasing risk of damage to macroinvertebrate community and ecosystem functionality. Furthermore, a scenario-based approach can be used by practitioners to quantify the likelihood of macroinvertebrate change into the future, thus aiding decision makers in their evaluation of strategy performance and impact. To ensure that a regulation strategy is well suited to the decision maker's tolerability to risk, the simulated hydrological indicator values, multi-level linear model and fitted residual distribution can be used to identify exceedance probabilities of achieving specific LIFE scores in the future ensembles. Using the visualisation tools presented in this paper, the decision maker can identify the likelihood of maintaining historically observed conditions and decide if the strategy sufficiently protects simulated LIFE scores against future environmental conditions.

There is considerable scope to improve the framework presented here. Firstly, whilst the proposed framework does include an estimation of the residual uncertainty from the multi-level linear regression model, it does not quantify the errors introduced from the wider modelling framework. A sensitivity analysis could be adopted in future applications of this framework to explore the sensitivity of simulated macroinvertebrate response to structural and parametric uncertainties within the climate-hydro-demand modelling framework (Pianosi et al., 2016).

Secondly, the hydro-ecological model presented here only considered flow statistics when predicting future LIFE score. Yet, dispersal effects (Ptatscheck et al., 2020), trophic interactions (Bruder et al., 2017), water temperature (White et al., 2017), chemical composition (Clews & Ormerod, 2009), and sediment supply (Larsen et al., 2009) influence river ecosystems to different extents. With sufficient data, the proposed framework could be expanded to consider a wider variety of environmental variables in the multi-level model development phase.

Thirdly, the regulatory requirements examined in the case study example presented here were adapted from existing policies that use a fixed threshold to allocate water throughout the year. Examination of more flexible regulatory policies that account for seasonality and variability in the flow regime could further improve water allocation for human consumption and freshwater ecosystems alike (Pastor et al., 2014). Therefore, future work could investigate regulatory arrangements that target features of the hydrological regime identified as important to maintaining LIFE scores. Upon selecting a regulation strategy, the water planner can use careful monitoring to ensure that key hydrological indicators are maintained at the level required to achieve acceptable LIFE scores.

Finally, the framework could also be used to enhance existing approaches of water supply investment and policy planning, which commonly trade-off metrics of water supply (e.g. risk, robustness) against the capital and operating cost of adaptation (Borgomeo et al., 2016; Herman & Giuliani, 2018; Matrosov et al., 2015; Mortazavi-Naeini et al., 2012). Macroinvertebrate response, as simulated here, could be used as a proxy for river health and incorporated into existing multi-objective planning approaches as an objective to maximize. The subsequent decision making framework could be used to identify water supply and demand management options that are robust to future uncertainties, whilst being cost effective, risk-averse and environmentally beneficial. This would provide a much needed move towards holistic water system planning that considers the complexity of interactions between hydrology, demand, water system management and riverine health.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crm.2021.100303.

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