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Assessing the relative importance of parameter and forcing uncertainty and their interactions in conceptual hydrological model simulations

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ABSTRACT

Predictions of river flow dynamics provide vital information for many aspects of water management including water resource planning, climate adaptation, and flood and drought assessments. Many of the subjective choices that modellers make including model and criteria selection can have a significant impact on the magnitude and distribution of the output uncertainty. Hydrological modellers are tasked with understanding and minimising the uncertainty surrounding streamflow predictions before communicating the overall uncertainty to decision makers. Parameter uncertainty in conceptual rainfall-runoff models has been widely investigated, and model structural uncertainty and forcing data have been receiving increasing attention. This study aimed to assess uncertainties in streamflow predictions due to forcing data and the identification of behavioural parameter sets in 31 Irish catchments. By combining stochastic rainfall ensembles and multiple parameter sets for three conceptual rainfall-runoff models, an analysis of variance model was used to decompose the total uncertainty in streamflow simulations into contributions from (i) forcing data, (ii) identification of model parameters and (iii) interactions between the two. The analysis illustrates that, for our subjective choices, hydrological model selection had a greater contribution to overall uncertainty, while performance criteria selection influenced the relative intra-annual uncertainties in streamflow predictions. Uncertainties in streamflow predictions due to the method of determining parameters were relatively lower for wetter catchments, and more evenly distributed throughout the year when the Nash-Sutcliffe Efficiency of logarithmic values of flow (lnNSE) was the evaluation criterion.

1. Introduction

The traditional understanding of water management is challenged by evidence of increasing nonstationarity in environmental systems (Milly et al., 2008). Modelling hydrological changes and their uncertainties is important for future water security (Wheater and Gober, 2013). Decision makers are increasingly interested in the uncertainty surrounding model predictions (Loucks et al., 2005), and so modellers are tasked with quantifying and communicating this uncertainty to inform water resources management and policy development (Willems and de Lange, 2007). However, details of the sources of uncertainty are typically not required by such end-users (Bruen et al., 2010). The onus is on modellers to understand the sources of uncertainty and therefore focus effort on reducing it, before communicating the overall uncertainty to end-users of streamflow predictions.

The uncertainties surrounding model outputs can have an aleatoric (e.g. measurement errors in forcing data) and/or epistemic character (e.g. omitted processes in model structures) and both are present in environmental modelling. In a model-based study, uncertainties can arise in (i) model context, (ii) model structure, (iii) forcing data and (iv) identification of parameter values (Walker et al., 2003). If the context of a study (including assumptions and boundary conditions) is defensible or justifiable, three dominant sources of uncertainty remain. The combination of these uncertainties in the modelling process produces its prediction error or predictive uncertainty (Todini, 2009). Understanding the three main sources of uncertainty and their interplay is necessary for an overall appreciation of the model prediction reliability. However, there are only a few studies that address all these facets (e.g. Butts et al., 2004).

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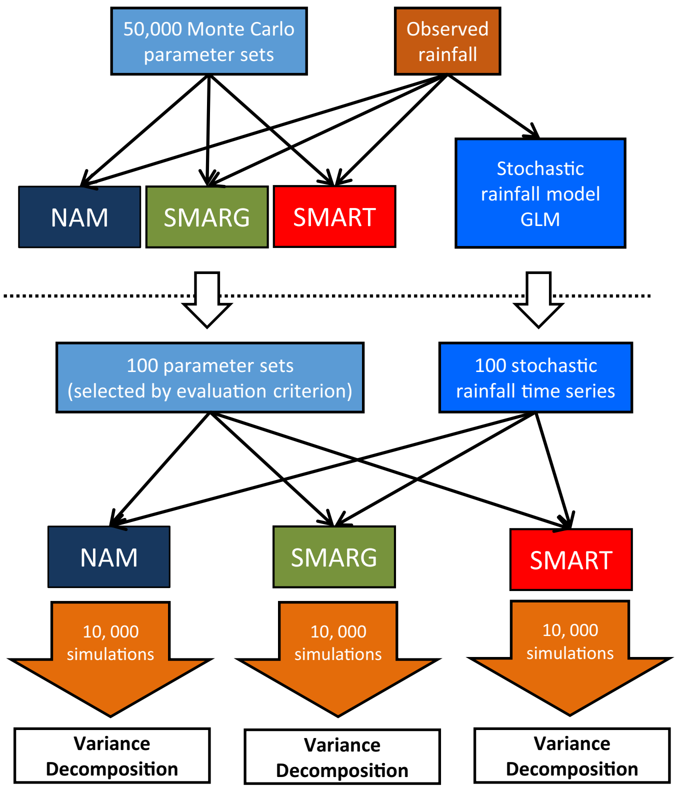

Fig. 1. Flow chart of methodology for variance decomposition.

Most studies have focused on one or two aspects of these uncertainty sources, for instance, uncertainty due to parameter estimation strategy has been widely studied in recent decades (Wheater et al., 1986; Wagener and Wheater, 2006; van Werkhoven et al., 2008; Sun et al., 2012; O'Loughlin et al., 2013). There is a growing body of literature investigating model structure uncertainty (Wagener et al., 2001; Clark et al., 2008; Breuer et al., 2009; Gupta et al., 2012), and more recent studies have investigated uncertainties in modelled streamflow due to both model structure parameter estimation strategy (Mendoza et al., 2015; Mockler et al., 2016), and model structure and forcing data (Renard et al., 2010).

Monte Carlo methods are frequently used to sample possible variations in forcing data and parameters using assumed probability distribution functions (e.g. GLUE methodology from Beven (2006)). Uncertainty assessments of forcing data has received relatively less attention than the effect of different model structures and parameters, and is mostly focused on precipitation as the dominant driving data (Kavetski et al., 2006; Chun et al., 2009; Younger, 2009; Sapriza-Azuri et al., 2013; Sapriza-Azuri et al., 2015), regardless of how estimated (Zappa et al., 2010), although there are some attempts to understand potential evapotranspiration (e.g. Chun et al., 2012). For this study, we have limited the investigation of forcing data to precipitation.

The objective of this study is to present an assessment of the relative importance of the sources of uncertainty in model predictions under a variety of plausible rainfall scenarios that may be used in studies, for example, of non-stationarity in hydrology. To do this, we combine stochastic rainfall ensembles (i.e. a collection of 100 rainfall time series simulations from specific weather states) and multiple parameter sets for three conceptual rainfall-runoff models (Fig. 1). In addition, we investigate the uncertainty interplay between the precipitation forcing and identification of hydrological model parameters by an analysis of variance model. In summary, this framework is used to decompose uncertainty in simulated streamflow into three components:

(i) uncertainty in simulated flow due to uncertainty about the forcing data, here limited to the precipitation data (U-forcing),
(ii) uncertainties due to the method of determining model parameters (U-parameters), and
(iii) uncertainties due to the interactions between the above sources i.e. forcing data and model parameters (U-interactions).

The proposed uncertainty assessment approach is applied to monthly average simulations of 31 catchments in Ireland. Ireland is used in this study because of the availability of quality controlled climatological and hydrological data over an extended area. Moreover, the heterogeneity in soils, geology and topography in Ireland provides a diverse range of exemplars of partitioning of net precipitation between surface and groundwater flow paths contributing to streamflow. To quantify the uncertainty of the precipitation forcing, we use a Generalised Linear Model (GLM) framework (Chandler and Wheater, 2002) which has been applied in Australia, North and South America, Europe and Africa (Yang et al., 2005; Frost et al., 2011; Chun et al., 2013; Kigobe et al., 2014). Moreover, the adopted spatial GLM approach was tested in Ireland (Yang et al., 2005). It is extended here to include synoptic of the predominant atmospheric circulation pattern using Lamb weather type information (Jones et al., 2013) for generating spatial precipitation time series for all 31 Irish catchments.

To see how the choice of hydrological model may influence the uncertainty in each model's parameters, three conceptual rainfall models are used. Conceptual catchment models can be useful for investigating any possible changes in hydrological responses (Wheater et al., 1993) and they can be a learning tool for studying process dynamics (Dunn et al., 2008). Because of their simplicity, such models are computationally inexpensive to use for exploring uncertainties (e.g. Chun et al., 2009). The three rainfall-runoff models selected were (i) the Nedbør–Afstrømnings-Model (NAM), (ii) the Soil Moisture Accounting and Routing with Groundwater model (SMARG) and (iii) the Soil Moisture Accounting and Routing for Transport (SMART). The first two models were selected for this study as they have been widely applied in Irish catchments (Goswami et al., 2005; RPS, 2008; Bastola et al., 2011; Mockler and Bruen, 2013; O'Brien et al., 2013). The SMART model (Mockler et al., 2016; Mockler et al., 2014) was also included in the model comparison as it was recently developed for Irish catchments.

The structure of hydrological models, originally developed for flood forecasting and water resources analysis without climate change, have been identified as contributing significantly to the overall uncertainty envelope of future climate change impact scenarios in Ireland (Bastola et al., 2011). This study aimed to decompose the uncertainty in hydrological simulations for Irish catchments, in order to;

(i) identify the relative importance of uncertainty in streamflow due to U-forcing, U-parameters and U-interactions and,
(ii) compare this uncertainty for three different hydrological models and two performance criteria.

Following this introduction, Section 2 details the data, models and methods used to generate the model ensembles and variance decomposition. Results and discussion are presented in Section 3, followed by conclusions.

2. Data, models and methods

2.1. Irish catchment data

Ireland has an area of approximately 70,000 km^2 with gently undulating lowlands located in the centre with elevations generally

Table 1
Catchment characteristics including AAR (Annual Average Rainfall) and mean discharge (Q).

ID	Catchment	Area (km^2)	AAR (mm yr^{-1})	No. rain gauges	Mean Q (m^{3}s^{-1})	% Missing Q data
1	Anner	437	913	3	6.8	3.6
2	Aughrim	203	1423	3	5.7	31.2
3	Bandon	424	1576	2	14.9	6.7
4	Barrow	2419	865	11	33.2	0.8
5	Blackwater	2334	1255	12	59.7	4.6
6	Bonet	264	1670	2	10.8	20.4
7	Boyne	2460	903	13	37.8	0.6
8	Bride	334	1305	5	9.5	1.6
9	Camlin	253	884	4	3.9	8.9
10	Clare	700	1146	3	16	11.8
11	Clodiagh	254	904	2	3.9	12.5
12	Dee	334	918	3	4.3	2.9
13	Deel Moy	151	1922	4	6.7	12.9
14	Deel Munster	439	1191	2	10.7	26
15	Erne	1492	1008	3	30.2	20.6
16	Feale	647	1532	3	22	14
17	Fergus	511	1135	2	10.4	2.3
18	Flesk	329	1897	2	14.4	6.9
19	Graney	280	1384	2	7.7	4.1
20	Little Brosna	479	962	3	8.3	23.6
21	Maigue	763	1018	4	13	10.5
22	Moy	1975	1313	9	58.8	8.4
23	Mulkear	648	1244	3	15.5	8.7
24	Nenagh	293	1041	2	6.4	28.5
25	Nore	2418	962	18	39.6	0.8
26	Rinn	281	1027	2	5.7	32.6
27	Robe	238	1220	4	6.2	5.5
28	Ryewater	210	820	7	2.4	6.8
29	Shournagh	208	1213	4	5.1	28.6
30	Suck	1207	1061	8	25.2	18.2
31	Suir	1583	1113	3	34	2.1
	Maximum	2460	1922	18	59.7	32.6
	Mean	437	1135	3	10.7	8.7
	Minimum	151	820	2	2.4	0.6

less than 150 m above sea level. Annual rainfall varies from in excess of 3000 mm in the western mountains to less than 1000 mm along the east coast. Mean annual temperatures range between 9 °C and 10 °C.

The 31 study catchments (Fig. 2, Table 1) were selected on the basis of having good quality meteorological and hydrometric data available for the study period, which is 15 years beginning from 1 January 1990. The chosen catchments cover over 35% of the area of the country and represent a wide variety of meteorological and geological conditions, with areas ranging from 151 km^2 to 2460 km^2.

Meteorological data consisted of daily rainfall and potential evapotranspiration values from Met Éireann for the study period. The catchment-area averaged rainfall was calculated using the Thiessen method (Thiessen, 1911), which has been show to provide comparable performance compared to more computationally demanding methods (Dirks et al., 1998). Each catchment has data from at least two precipitation stations and the largest (Boyne) contains 13 stations. Annual average rainfall (AAR) ranges from 820 mm in the Ryewater to 1897 mm in the Flesk (average of 1189 mm). Fig. 3 shows the range of monthly rainfall amounts across the catchments. Potential evapotranspiration (PE) was calculated by Met Éireann at 14 synoptic weather stations according to the FAO Penman–Monteith method (Allen et al., 1998). PE data from the nearest station was selected for each catchment and assumed spatially uniform. Actual evapotranspiration is calculated by the hydrological models as a function of PE and soil moisture storage.

Hydrometric data for each catchment consisted of daily mean flows supplied by the Office of Public Works (OPW) and the Environmental Protection Agency (EPA). Periods within the 16 years of the study with missing flow data were not included in the analysis. Of the 31 catchments, four have missing flow data for over 25% of the study period, with the majority having less than 10% missing values (Table 1). These gaps have no significant flow rate or seasonal trends and are not suspected of introducing any bias.

2.2. Rainfall models

Regional and local precipitation patterns are linked to atmospheric circulation patterns (Sapriza-Azuri et al., 2013; Sapriza-Azuri et al., 2015; Hay et al., 1991; Bardossy and Plate, 1992; Corte-Real et al., 1999; Fowler et al., 2000; Bellone et al., 2000; Barry and Chorley, 2003; Fowler et al., 2005; Yang et al., 2010). Many advanced stochastic rainfall modelling approaches provide outputs which can capture the different statistical signatures of each weather type. For example, using Lamb weather types (Jones et al., 2013; Jenkinson and Collinson, 1977; Jones et al., 1993; Kalnay et al., 1996), daily precipitation ensembles have been generated for Yorkshire, the United Kingdom (Fowler et al., 2000) and the Upper Guadiana Basin, Spain (Sapriza-Azuri et al., 2013).

In this study, 31 spatially dependent time series are generated for the 31 catchments using the spatial GLM framework (Chandler and Wheater, 2002; Yang et al., 2005) which was used in Ireland (Chandler and Wheater, 2002). In a new attempt to extend this framework, Lamb weather type information are used to condition the spatial GLMs, which include information of the predominant synoptic atmospheric circulation patterns over Ireland (Fowler et al., 2005; Yang et al., 2010). The GLM structures can be defined in terms of internal structures and external interactions. The internal GLM structures describe temporal and site effects. Fourier series (sines and cosines) model the timing (phase) and magnitude of seasonal effects. Previous day precipitation occurrence states and amounts are the internal variables to account for temporal autocorrelations. Legendre polynomials of latitude and longitude are used

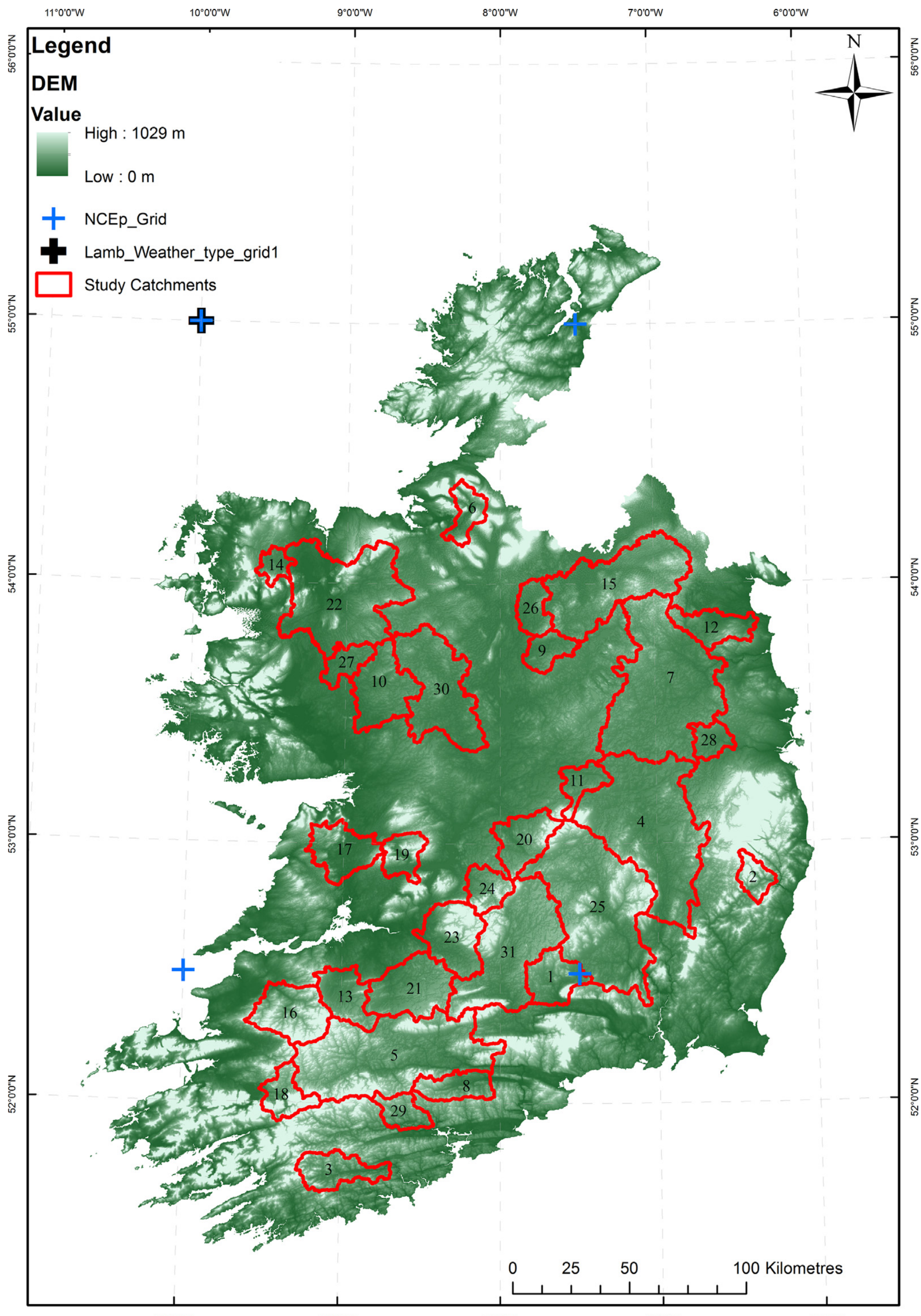

Fig. 2. Locations of study catchments (Source of elevation map: EPA).

for the site effects. When Legendre polynomials are used, all the lower order terms must have been included before higher order terms are included in the precipitation model. For each time step, the precipitation occurrence probability (p_i) is determined by:

$$\ln\left(\frac{p_i}{1-p_i}\right) = x_i^T \beta \tag{1}$$

where $\mathbf{x_i}^\mathbf{T}$ is the *i*th day transposed predictor vector which consists of spatiotemporal structures and external driving climate variables and $\boldsymbol{\beta}$ is the logistic regression coefficient vector. In the amounts model, the mean rainfall value of the ith wet day (μ_i) are modelled by the gamma distribution. Using a log link function and a constant shape factor, the mean rainfall value (μ_i) is conditioned by the ith day environmental conditions ($\boldsymbol{\xi}$) and is expressed as:

$$\ln(\mu_i) = \xi_i^T \gamma \tag{2}$$

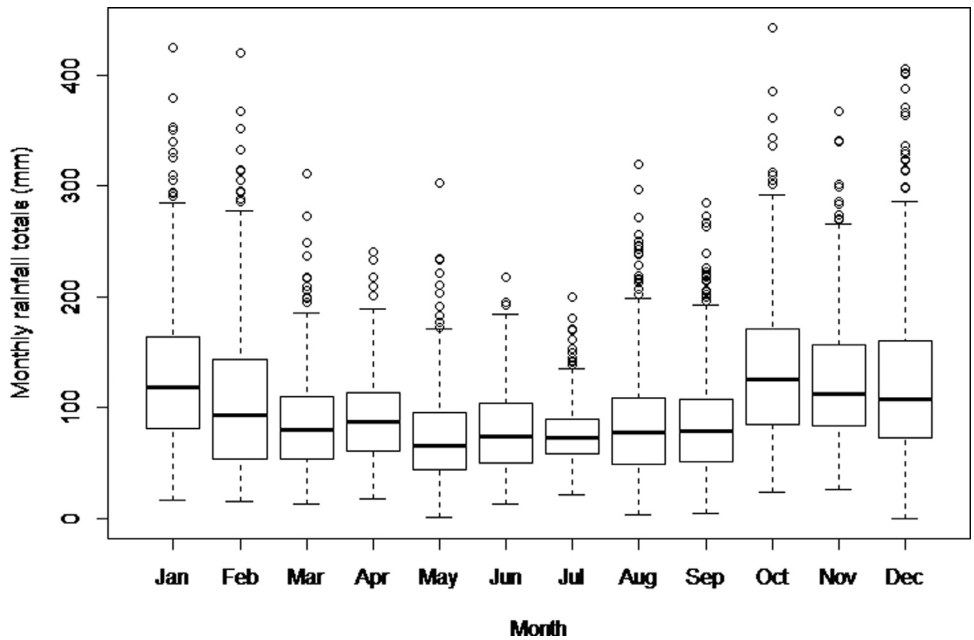

Fig. 3. Monthly rainfall distribution of 31 catchments for 16 year study period.

where $\boldsymbol{\xi}_{\mathbf{i}}^{\mathbf{T}}$ is the *i*th day transposed predictor vector which consists of spatiotemporal structures and external driving climate variables and $\boldsymbol{\gamma}$ is the gamma regression coefficient vector.

Spatial dependence of occurrences is modelled by logistic regressions conditioned by the mean of site probabilities and the weather states (wet or dry) of other sites. For the amounts model, a correlation ρ(i,j) function based on distance (d_{ij}) between i and j is expressed as:

$$\rho(i, j) = \alpha + (1 - \alpha)\exp(-\phi d_{ij}^{k}) \quad (3)$$

where α, ϕ and k are the parameters of a k-powered decay function.

Various external climate variables were further added to the precipitation model after the internal structure was defined. Ten long non-blend precipitation time series for longer than 40 years from the European Climate Assessment & Dataset (ECA&D, 2014) were used to test the potential of climate predictors including ten northern hemisphere teleconnection indices (Barnston and Livezey, 1987) and the derived Lamb Weather Types based on Jones, Harpham (Jones et al., 2013). These data were used instead of the 15-year study catchment rainfall time series in order to assess the effects of climate cycles for the precipitation model structure formulation. The indices are listed in Table 2.

For conditioning precipitation simulation using weather types, the Lamb indices derived from the National Centers for Environmental Prediction (NCEP) data were used (Jones et al., 1993). These weather type schemes (Jones et al., 2013) are based on reanalysis products and allow future possible extensions using other gridded climate products. Here we aggregate the daily Lamb indices to monthly occurrences for eight directional and six vortical weather types (Table 2). The 14 monthly weather type time series are highly correlated because they are compositional data (i.e. when one weather type increases, other types must decrease). Therefore, before applying them to the precipitation model, a factor and cluster analysis was used to reduce the 14 weather type time series to a set of representable weather types (see Appendix B). The directional and vortical weather types were separated into different factors. These account for 35 and 65% total variance, respectively. The chosen four weather types for further precipitation modelling are the northerly (L_N), westerly (L_W), anticyclone (L_A) and cyclone (L_C) weather states. They explained around 60% of total variance of all the weather types. Apart from including the anticyclone types, the selected weather types are similar to the realistic weather groups used in Fowler et al. (2000).

Table 2
Possible external climate variables.

Ten teleconnection indices
North Atlantic Oscillation (NAO)
East Atlantic Pattern (EA)
West Pacific Pattern (WP)
EastPacific/ North Pacific Pattern (EP/NP)
Pacific/ North American Pattern (PNA)
East Atlantic/West Russia Pattern (EA/WR)
Scandinavia Pattern (SCA)
Tropical/ Northern Hemisphere Pattern (TNH)
Polar/ Eurasia Pattern (POL)
Pacific Transition Pattern (PT)
Lamb indices for weather types
Directional
1 -> N (directional)
2 -> NE (directional)
3 -> E (directional)
4 -> SE (directional)
5 -> S (directional)
6 -> SW (directional)
7 -> W (directional)
8 -> NW (directional)
Vortical
9 -> C (Cyclonic)
10 -> A (AntyCyclonic)
11 -> HYC (Hybrid Cyclonic)
12 -> HYA (Hybrid Anticyclonic)
13 -> UC (unclassified Cyclonic)
14 -> UC (unclassified Antyciclonic)

For selecting external climate variables, each of the possible variables is included in the precipitation model individually. Only individual variables which proved to be statistically significant (p-value < 0.05) were then used as initial models for stepwise regressions in which the minimum p-value for a variable to be added and removed is 0.05. Generally, the possible climate variables are not strongly correlated because the teleconnection indices are the results of Empirical Orthogonal Functions (EOFs) and the four weather types are selected from the factor analysis. The final models are not very different from the initial models although the final identified precipitation model may still be just a local optimum model having reasonable variables instead of the 'best' predictors for interpretation (See Draper and Smith, (1998) and Chun, (2011) for more discussion). The precipitation model structure identified from the long non-blend precipitation time series was then calibrated using the 31 station time series for generating catchment precipitation ensembles. Further details on the GLM rainfall simulation framework and the variable selection methods are provided in Appendix A and B, respectively.

2.3. Conceptual rainfall-runoff models

Conceptual Rainfall-Runoff (CRR) models typically consist of a set of equations describing a simplified representation of hydrological processes at catchment scale. Lumped models treat the catchment as a uniform unit (Wheater, 2002) with all variables treated as averages over the catchment. Three such models with different structures are investigated in this study. Each model receives forcings of catchment average rainfall and potential evapotranspiration values at daily time-steps. The models calculate actual evapotranspiration, change in volume of stored water in their various components and total runoff, also at daily intervals. Further details on the model structures, including schematics, and analysis of parameter sensitivities can be found in Mockler et al. (2016).

2.3.1. NAM model

The 'Nedbør-Afstrømnings-Model' (NAM) (Nielsen and Hansen, 1973) is widely used and has been previously applied in Irish catchments for investigating the contributions of groundwater and surface water to streamflow (RPS, 2008; O'Brien et al., 2013). The NAM structure used in this study has two storage reservoirs for soil moisture accounting and reservoirs to represent four hydrological pathways. The model parameters include eight parameters controlling the moisture content in storages representing the surface, soil and groundwater storages, and three parameters relating to the routing components.

2.3.2. SMARG model

The Soil Moisture Accounting and Routing with Groundwater component (SMARG) model was developed in NUI Galway (Khan, 1986; Kachroo, 1992; Tan and O'Connor, 1996). It has a soil moisture accounting component which represents the catchment as a vertical stack of individual soil layers, each of which can contain an amount of water up to a predetermined limit. This component keeps account of the rainfall, evaporation, runoff, and soil storage processes using six parameters. The routing component uses three parameters to simulate the attenuation effects of the catchment by separately routing the surface and groundwater generated by the soil moisture accounting component through linear reservoirs.

2.3.3. SMART model

The SMART model (Mockler et al., 2016; Mockler et al., 2014) was developed as a hydrological model especially for water quality simulations. The model emphasises the identification of individual hydrological flow path contributions. The proportions of streamflow attributed to surface or sub-surface flow are important when coupling flow simulations with nutrient attenuation equations, as the mobilisation and attenuation of nutrients and sediment varies significantly depending on runoff flow path (Medici et al., 2012; Futter et al., 2014). SMART simulates hydrological flows using conceptual soil moisture accounting equations based on a number of soil moisture layers, following the style of SMARG and its predecessors. The depths of these soil moisture layers vary depending on catchment characteristics, and represent the average conditions over each catchment. The numerical processes of the four conceptual flow paths use 10 parameters in total, four of which relate to flow routing.

2.4. Hydrological model evaluation and parameter selection

For each model, 50,000 parameter sets were generated from Sobol' sequences of standard ranges of values outlined in Mockler et al. (2016) that encompass high performing combinations for Irish catchments. Data for each of the 31 catchments were simulated using the same 50,000 parameter sets for each of the NAM, SMARG and SMART models and evaluated against streamflow using two criteria. Two groups of 100 behavioural parameter sets for each catchment, one for each of the performance criteria, were then selected from the original 50,000 sets, resulting in an ensemble of catchment outflows for each model and criterion at a daily time-step for the 15 year study period (with one year warm-up). Precipitation uncertainty is included in the subsequent step of the methodology for variance decomposition, described in Section 2.5 below, by using simulated rainfall time series from the GLM. Firstly, for each hydrological model evaluation, each simulated output was compared with the corresponding measured output from the catchment and values for two criteria were calculated. The Nash Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970) is a widely-used goodness of fit measure based on the error variance, and is defined as:

$$NSE = 1 - \frac{\sum_{t=1}^{n} (Q_{o,t} - Q_{m,t})^2}{\sum_{t=1}^{n} (Q_{o,t} - \overline{Q_o})^2}$$

where $Q_{o,t}$ is the observed flow for time-step t, $Q_{m,t}$ is the modelled flow at time-step t, $\overline{Q_o}$ is the mean observed flow and n is the length of the time series. The second criterion was the Nash Sutcliffe efficiency with log values (lnNSE) (Krause et al., 2005). The original NSE criterion evaluates the correlation of the time series with an emphasis on peak flows, whereas the lnNSE gives more weight to low flows.

From the 50,000 simulations, the 100 results with the best values of each performance criterion were selected as representative high-performing parameter sets for each the three hydrological models. These are called the behavioural parameter sets. The analysis of variance was repeated for each group of behavioural parameter sets identified. For each model, these groups provide ranges of parameter values for assessing uncertainty and interactions. This Monte Carlo approach was subjectively chosen over a traditional optimisation routine as the top 100 parameter sets from optimisation, as expected, produced a much tighter clustering of parameters and simulated outflows, and so resulted in much lower parameter uncertainty estimates in the variance decomposition results.

2.5. Variance decomposition

This study used stochastic rainfall ensembles and multiple hydrological models to identify the relative importance of different sources of uncertainty on streamflow predictions (Fig. 1). For the analysis of variance, all possible combinations of each of 100 precipitation simulation runs (see Section 2.2 for details) and 100 behavioural hydrological parameter sets (see Section 2.4 for details) were used to generate 10,000 simulations from which the sensitivity indices were computed. The analysis of variance was repeated on behavioural parameter sets for two evaluation criteria.

The variance in the flow simulation ensembles of 10,000 simulations for each model (100 rainfall forcings and 100 hydrological model parameter sets) is decomposed into the various uncertainty contributions, i.e. due to U-forcing (precipitation data), U-parameters and U-interactions. The uncertainty in U-forcing and U-parameters is represented by their ensemble variance. Based on the law of total variance (e.g. Chun, 2011; Von Storch and Zwiers, 1999), a sensitivity index (SI) (Saltelli et al., 2004) representing the importance of the driving variable i (X_i) to the output (Y) can be defined by:

$$SI_i = \frac{Var(E(Y|X_i))}{Var(Y)}$$

where Var(.) and E(.) are variance and expectation functions respectively. In the sensitivity literature, $Var(E(Y|X_i))$ is usually referred to as the main effect of X_i. Similar approaches or indices have been used to decompose sources of uncertainty in other hydrological studies (e.g. Chun et al., 2010; Bosshard et al., 2013). Here, the uncertainty in the simulated flow is decomposed between U-forcing (SI_p), U- parameters (SI_ϕ) and U-interactions ($SI_{p\phi}$), and they can be expressed as:

$$SI_p + SI_\phi + SI_{p\phi} = 1$$

Theoretically, the hydrological model uncertainty (SI_m) could also be considered in the variance decomposition. However, this would only relate to the differences between the three model structures presented here, rather than a full assessment of model uncertainty which would include missing or misrepresented processes in the model structures. In this study, the effect of model choice is limited to a qualitative comparison of the SI results from the U-forcing, U-parameters and U-interactions for each model.

3. Results and discussion

3.1. Rainfall model performance

Table 3 summarises the final precipitation model structure. For the occurrence model, only a first order Legendre polynomial is needed to represent spatial variation in the meridional (East_West) direction. However, a combination of first, second and third orders Legendre polynomials are needed to capture spatial variation in the zonal (North_South) direction. Hence, the spatial variation of occurrence should be higher for the zonal than the meridional direction. For the precipitation amount model, both zonal and meridional site effects can be satisfactorily represented by a combination of first and second order Legendre polynomials. Fig. 4 shows the precipitation amount (black dots), and the fitted spatial correlation model (Eq. 1) appears to fit the residuals well.

The East Atlantic (EA) pattern is significant for both precipitation occurrences and amounts, whereas the Scandinavia pattern is only significant for the amounts model. The significant teleconnection identified for catchments representing the entire country is different from that in Chandler and Wheater (2002), who identified the North Atlantic Oscillation (NAO) as the driving climate variable for catchments in the West of Ireland, which are strongly influenced by weather from the prevailing South-Westerly direction. For the 31 modelled catchments, although the NAO is generally significant for the precipitation series between 53 and 55° north latitude (including Birr and Sligo as investigated in Chandler and Wheater (2002)), the southern precipitation time series are not significantly related to the NAO. The East Atlantic (EA) and Scandinavia patterns are better related to all 31 modelled precipitation series. For the weather types, the cyclone and anticyclone states are significant for the precipitation occurrences, and the anticyclone state is the only significant weather type for the precipitation amounts.

Table 3
Final precipitation model structure.

a) Occurrence model	
1	Constant
2	Teleconnection: East Atlantic Pattern (EA)
3	Weather type: Cyclone
4	Weather type: Anticyclone
5	First order of Legendre polynomial representation for Easting
6	The first, second and third order of Legendre polynomial representation for Northing
7	Daily seasonal effect, cosine component
8	Daily seasonal effect, sine component
9	Previous day precipitation occurrence indicator for daily temporal effects (I(Precipitation[*t*-1]> 0))
10	Precipitation occurrence threshold (0.5 mm)
11	Parameter in the logistic model based on conditional independence given weather state and the mean of the site occurrence probability
b) Amounts model	
1	Constant
2	Teleconnection: East Atlantic Pattern (EA)
3	Teleconnection: Scandinavia Pattern (SCA)
4	Weather type: Anticyclone
5	First and second order of Legendre polynomial representation for Easting
6	First, second and third order of Legendre polynomial representation for Northing
7	Daily seasonal effect, cosine component
8	Daily seasonal effect, sine component
9	Previous day precipitation accounts with a logarithm transformation (Ln(1+Y[*t*-1]))
10	Dispersion parameter
11	Three parameters in the correlation function for precipitation amount residuals (Eq. 3)

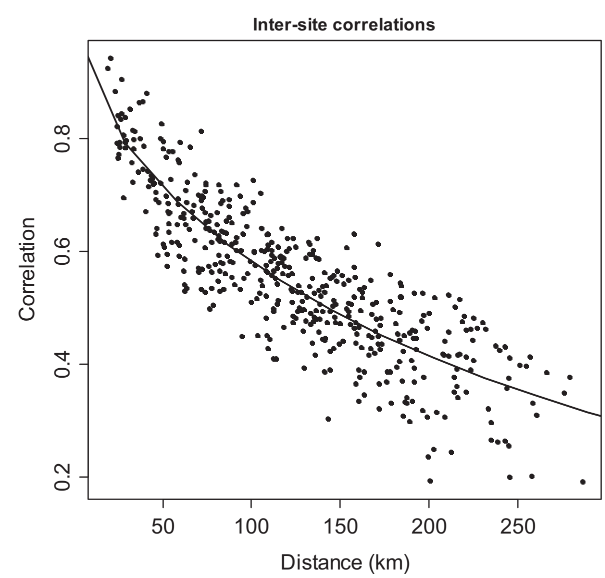

Fig. 4. Rainfall model output performance: amount (black dots), and fitted spatial correlation model (black line).

The effects of the climate variables on the precipitation ensembles are shown in Fig. 5. The colour bands show the quantiles of 100 precipitation time series and the black lines are the observed historical precipitation mean for all 31 catchments. If the simulation ensemble encloses the observed statistics (black lines), the simulation is considered to be adequate. The precipitation model is calibrated using the data between 1996 and 2005. The data between 1990 and 1995 (the validation period) are not used for precipitation model parameter estimation. The quality of simulations is evaluated qualitatively by whether 95% of the ensemble

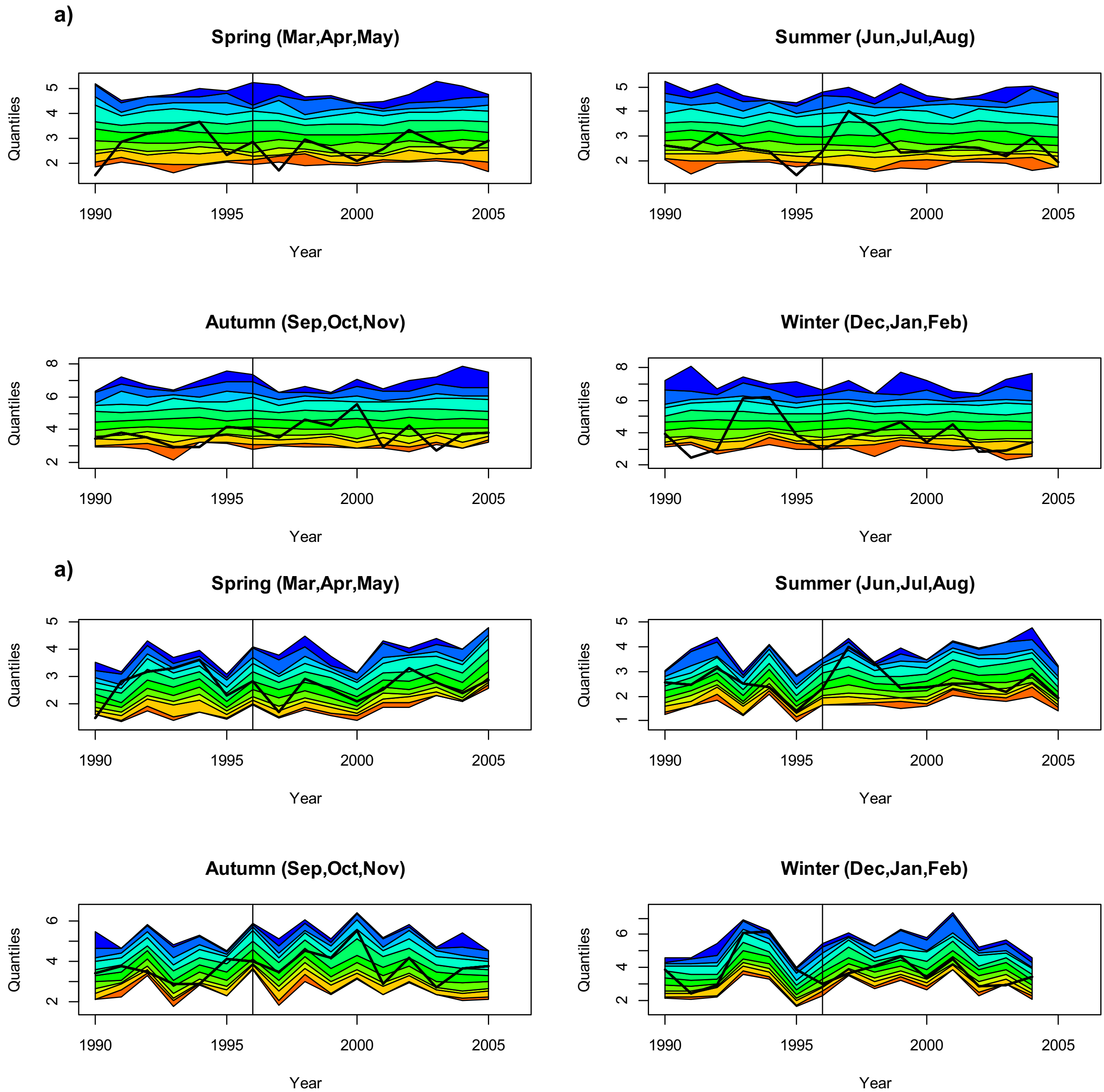

Fig. 5. Effects of climate variables on precipitation ensembles without external climate variables (5a) and with external climate variables (5b). Colour bands show quantiles of 100 precipitation time series and black lines are the observed historical precipitation mean for all 31 catchments.

runs enclose the observed precipitation (Fig. 5). In Fig. 5a, when the teleconnection information is not included, the simulations fail this test for the 1995 summer and the 1991 winter. When the teleconnection information is included, the observed precipitation is better captured (Fig. 5b). Nevertheless, both Figs. 5a and 5b do enclose the observations fairly well. Generally, the daily mean, standard deviation, maximum and first, second and third order of autocorrelations of the simulated daily precipitation ensemble match the observations. Although the simulated November standard deviation and the May and December autocorrelations may be slightly low, the overall daily precipitation simulation are fairly consistent with the observed precipitation statistical properties.

For the overall spatial patterns, Fig. 6 provides a comparison between historical annual sums and the average of simulated annual sums. Although the Boyne, Clodiagh and Nenagh simulations are slightly dryer and the Anner is slightly wetter than the observed, the observed and simulated spatial precipitation patterns are fairly coherent.

3.2. Hydrological model performance

In order to ultimately produce streamflow predictions, several subjective choices are made by hydrological modellers. A set of these choices, two models and two evaluation criteria, are compared in this study. Several other subjective choices, such as the

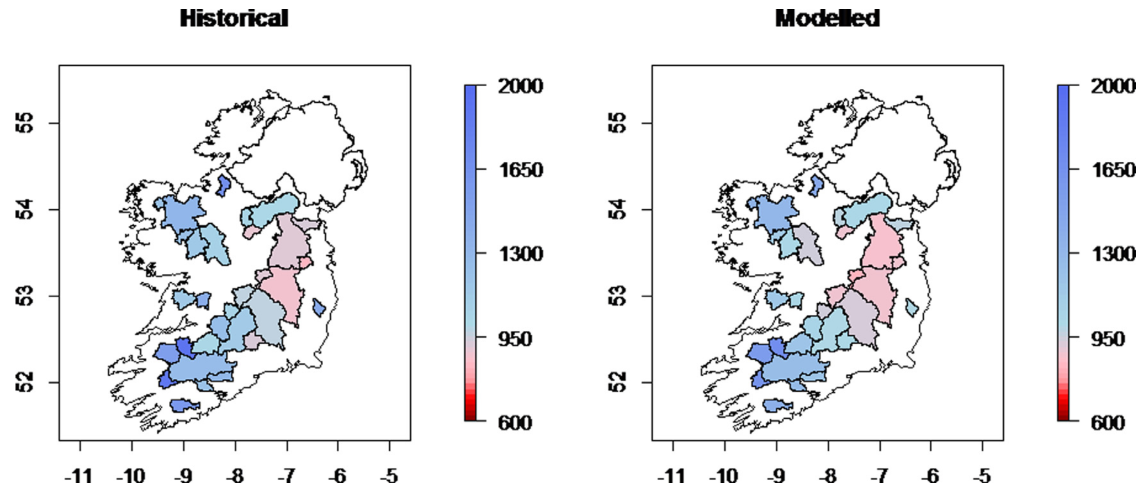

Fig. 6. Rainfall model output performance: spatial pattern of historical annual average rainfall and the average of simulated annual average rainfall.

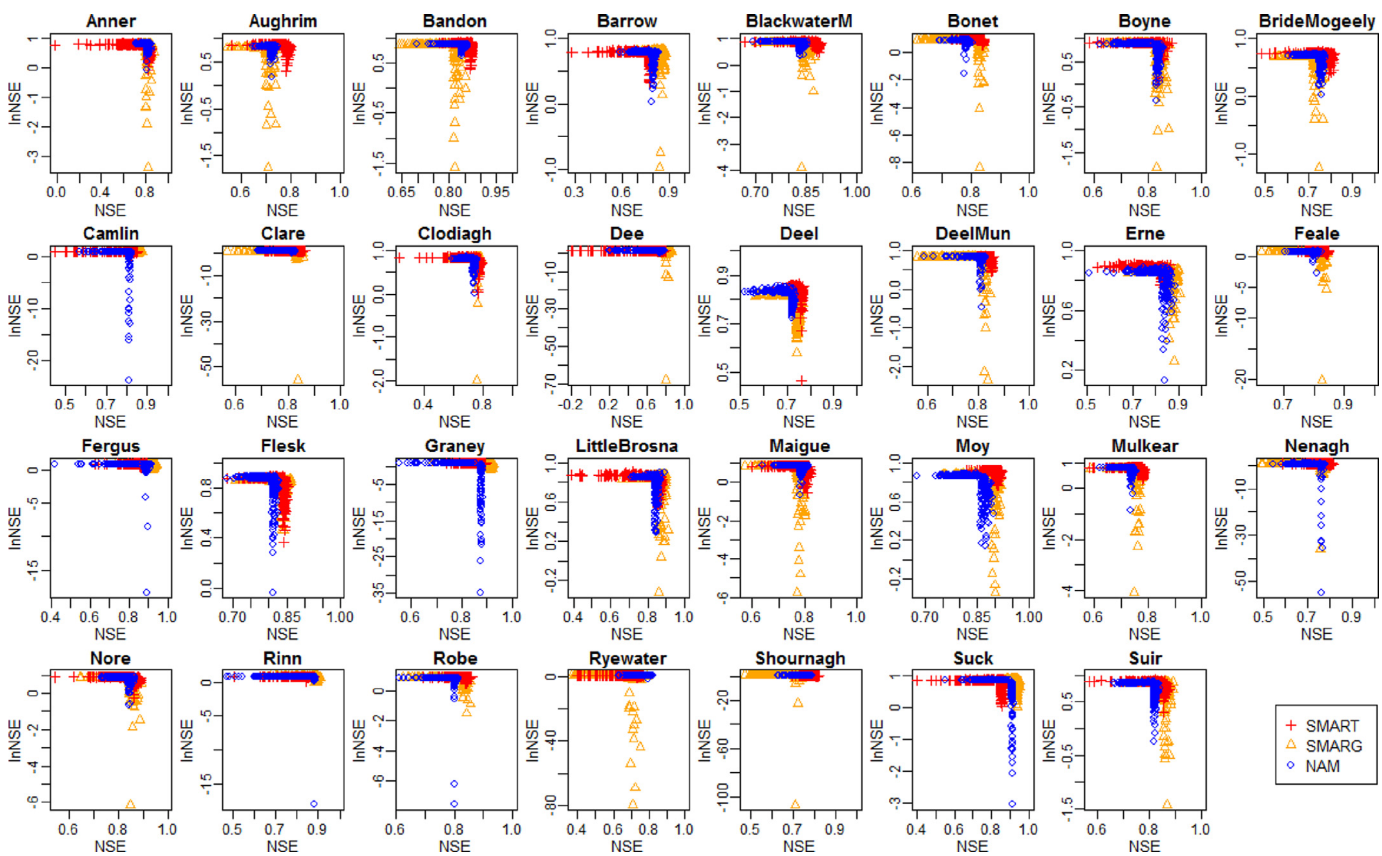

Fig. 7. NSE and lnNSE evaluation results from 200 simulations of the NAM (blue), SMARG (yellow) and SMART (red) models using observed rainfall forcings for 31 catchments.

number of parameter sets, were not included in this comparison and therefore the uncertainties due to these are not unexplored in the results.

Behavioural (i.e. the top 100 best performing) parameter sets for each of the three hydrological models were selected by ranking the fit of each of the 50,000 Monte Carlo simulations to the observed flow data, evaluated using (i) NSE and (ii) lnNSE criteria. The NSE and lnNSE results had no significant correlations between each other, indicating that the criteria evaluate different aspects of the hydrograph (Krause et al., 2005). Flow simulations produced by each of these best performing 100 parameter sets for both criteria were further examined for use in the uncertainty assessment. For the NSE set, the median NSE values for the NAM, SMARG and SMART models were 0.82, 0.85 and 0.84 respectively and for the lnNSE set, the median lnNSE values were 0.79, 0.83 and 0.88 respectively, with results varying between catchments in both cases.

The trade-offs between the two objective functions were examined by comparing criteria results for both behavioural sets, which showed that each model had some parameter sets that produced

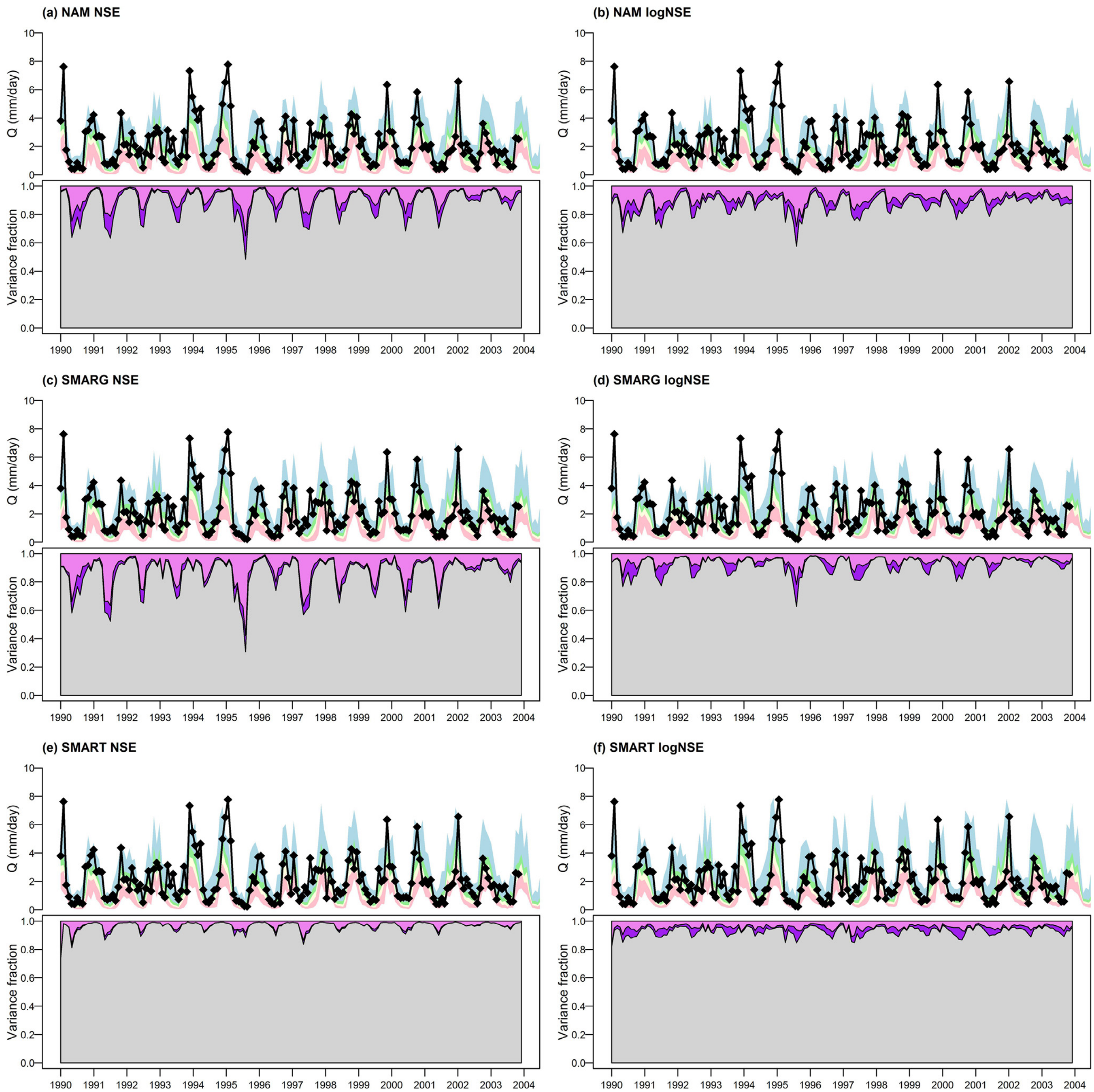

Fig. 8. Results of 10,000 ensemble simulations using NSE and lnNSE parameter sets for 3 models for one catchment (Mulkear). Upper Panel of (a-f): Colour bands show the 1st, 25th, 50th, 75th and 99th percentiles and observed average monthly streamflow values are in black. Lower Panel of (a-f): Uncertainty decomposition of simulations using (i) NSE and (ii) lnNSE parameter sets for the Mulkear catchment showing uncertainty due to U-forcing (grey), U-interactions (purple) and U-parameters (pink). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

high values for both NSE and lnNSE (Fig. 7). For these 200 simulations, (100 best for NSE plus 100 best for LnNSE) the SMART model generally produced the tightest clustering of results for the study catchments. This was partly because some parameters sets of the NAM and SMARG models that produced high NSE values also produced very low lnNSE values (e.g. the SMARG results for Ryewater catchment, Fig. 7).

The issue of over-parameterisation of conceptual hydrological models has been widely discussed (e.g. Beven, 2006; Kirchner, 2006), and this study includes these uncertainties within a broader investigation. Limitations in this method of assessing the hydrological models include the omission of uncertainties due to observation errors in the precipitation and streamflow, and the estimation of the average rainfall for each catchment. In this study, it is assumed that these sources of uncertainty are relatively small compared to the U-forcing, U-parameters and U-interactions examined here. However, these assumptions could be tested in future work.

3.3. Uncertainty decomposition of rainfall and hydrological model ensembles

Simulations were generated for each catchment using two groups of 100 behavioural parameter sets with 100 simulated rainfall time series. Fig. 8 (upper panels) shows an example of monthly time series produced for each model. The seasonal patterns of the observations are mostly captured by the 95% confidence bounds of the 10,000 simulated streamflow ensembles. All models and parameter groups underestimated some peak winter flows in the Mulkear catchment, particularly in 1995, which may be influenced by errors in measured precipitation or flows.

In our specific setup, the decomposition of the time-series of modelled streamflow shows that the majority of the uncertainty in flow simulations was attributed to uncertainties due to U-forcing, followed by U-parameters and U-interactions for both NSE and lnNSE. The average U-Forcing sensitivity for NSE was 91% (NAM), 89% (SMARG) and 94% (SMART), and for lnNSE was 88% (NAM), 90% (SMARG) and 92% (SMART) (e.g. Fig. 8 lower panels). This was to be expected given the dominance of stochastic variance in the rainfall time series in this region, and the allowed variability in the simulated rainfall time-series.

The following sections detail the relative importance of the sources of uncertainty and how these (i) differ between catchments, (ii) between models and (iii) over time by assessing monthly changes.

3.3.1. Changes in uncertainty decomposition across a hydroclimatic gradient

Similar to other studies (e.g. Mendoza et al., 2015), these results show that uncertainty decomposition is basin dependant. For these 31 study catchments, the uncertainties due to U-forcing increase for all models as catchment annual average rainfall (AAR) increases ($R^2 = 0.62$ for NSE and 0.73 for lnNSE). The sensitivity to U-parameters and U-interactions have the inverse relationship. Fig. 9 shows a similar relationship with U-Parameters sensitivity decreasing with increasing river discharge per unit area for each catchment. This is likely due to the greater contribution from the more linear quick-flow components of the hydrological models in these wetter catchments. Evapotranspiration is considered the most difficult aspect of the water balance to measure spatially, due to the complex interactions between climate, vegetation and soil conditions (Mills, 2000), and hence the inclusion of the evapotranspiration forcing data in the decomposition is recommended for future studies.

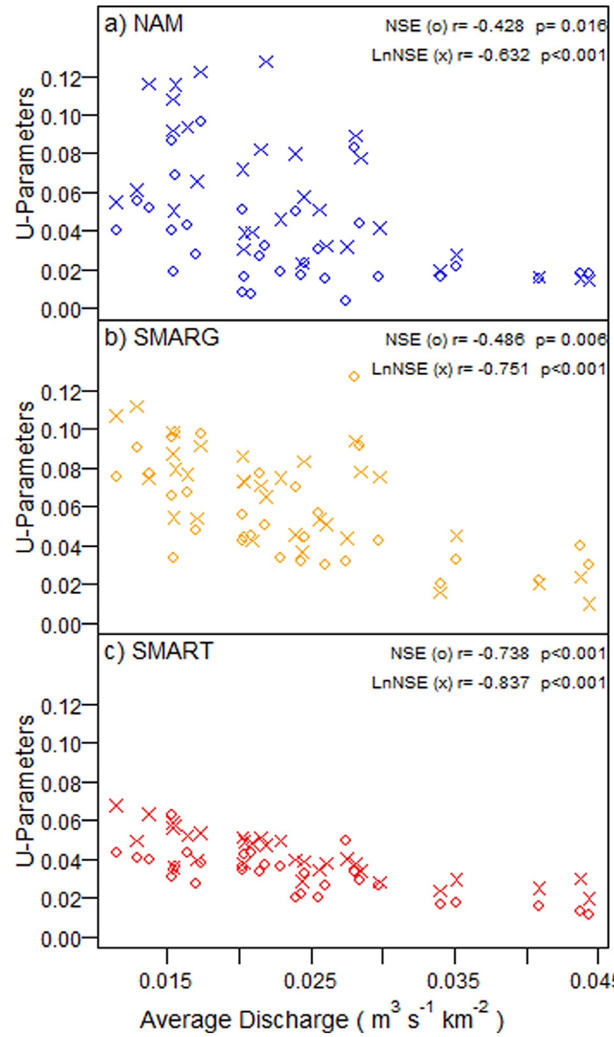

Fig. 9. Changes in fraction of U-parameter with average discharge for each catchment, illustrating decreasing U-parameter values for wetter catchments.

3.3.2. Comparison of uncertainty due to parameters for 3 models

In contrast to Mendoza et al. (2015) who showed that U-Parameters can contribute a similar or larger proportion of uncertainties compared to choice of conceptual model, results from this study show that there is a greater variation in U-Parameters caused by the model selection than by the choice of criteria for comparing with measured discharges. Model performance was not a strong predictor of the degree of U-parameter. For example, results for the Mulkear Catchment show NSE values are higher for the SMARG model than NAM (Fig. 7), but SMARG also has higher U-parameters (Fig. 8). This is a warning against depending only on good values of fitting criterion for confidence in models. The number of hydrological model parameters of the NAM (11), SMARG (9) and SMART (10) models did not indicate relative U-parameters. Although no single model was superior for all catchments, the SMART model performed best on average with lower U-parameter uncertainties, which is attributed to the tailored equations used to simulate the dominant processes in Irish catchments.

3.3.3. Monthly changes in uncertainty decomposition

To investigate the seasonality of parameter uncertainty, median monthly values were calculated from the best NSE and lnNSE parameter sets selected for each model (Fig. 10). When the NSE criteria is used to identify the behavioural parameter sets, simulations show a stronger seasonality compared to when the lnNSE is used, particularly with the SMARG and SMART models. This seasonal variation is seen in many catchment and models, where streamflow uncertainty from U-parameters and U-interactions increases during drier periods in the summer months from June to August (e.g. Fig. 8 lower panels). Uncertainty is reduced during higher rainfall in winter months as the conceptual moisture stores are saturated and the linear quick flow components dominate runoff generation.

A study by Bastola et al. (2011), which included the NAM model, concluded that hydrological model structures and parameterisation contribute significantly to the overall uncertainty envelope of climate change impact scenarios. This, and many other streamflow assessment studies, used hydrological models that were originally developed for high and flood flow regimes (e.g. NAM and SMARG), and used the NSE for evaluation. When predictions of low flows are of interest, the NSE performance criterion is shown to increase the uncertainties due to hydrological parameters (Fig. 10). Effects of this were reported in Steele-Dunne et al. (2008), where NSE was used to select 100 behavioural parameter to assess climate change impacts on hydrology in Irish catchments using the HBV-Light hydrological model. Validation and forecasting ensembles produced much greater parameter uncertainty for drier months compared to the wetter winter period, with authors reporting that the “impact

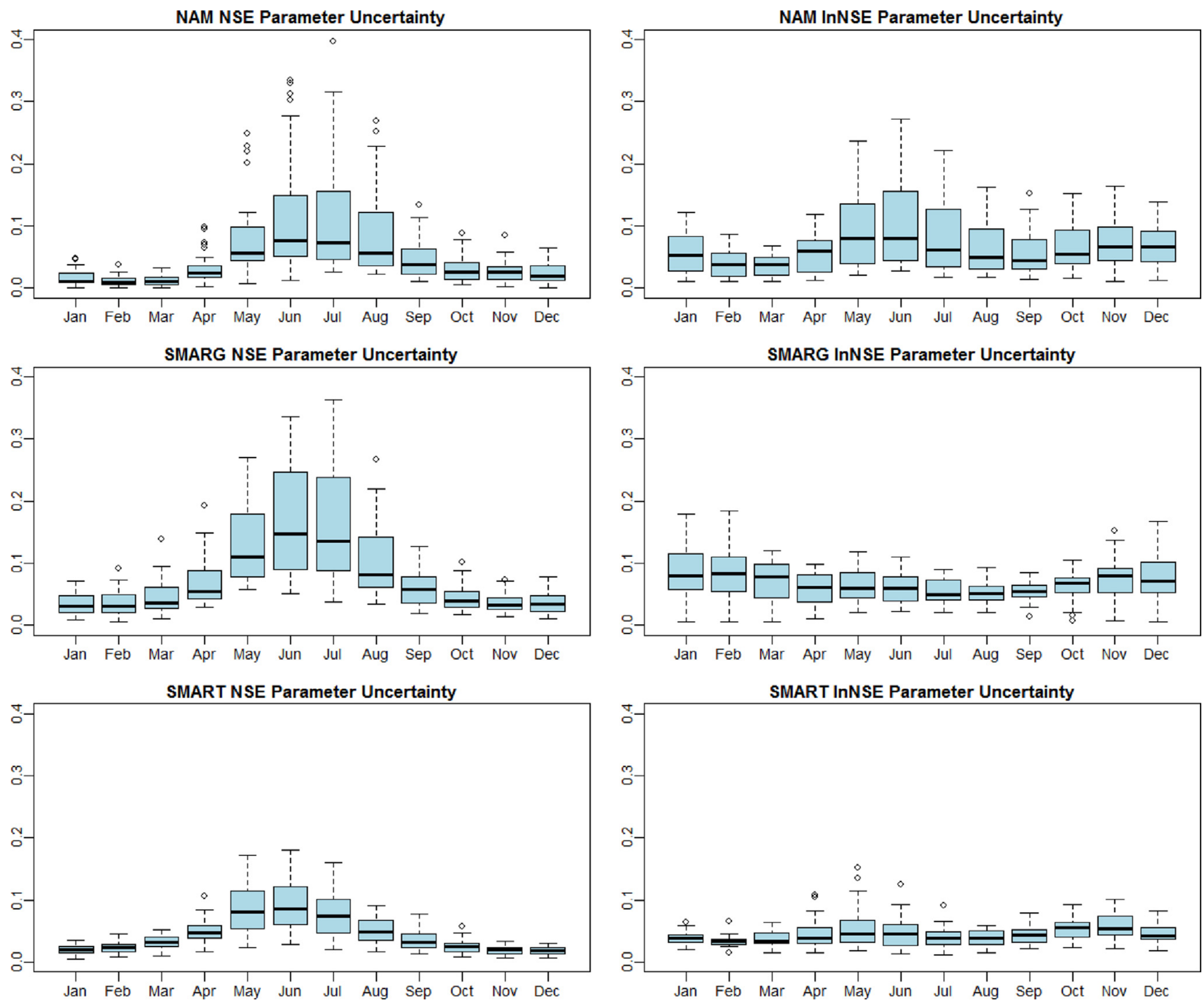

Fig. 10. Comparison of median uncertainties due to parameters for 3 models and 2 criteria for the 31 catchments.

of parameter uncertainty was very different in winter and summer".

Previous predictions from climate change impact studies for Ireland show a decrease in streamflow during the summer months, particularly in the east and south east (e.g. Bastola et al., 2011; Steele-Dunne et al., 2008; Charlton et al., 2006). Results presented here suggest that the performance criteria for parameter identification can be selected to reduce uncertainties in the flow regime of interest, relating to the focus of a particular study. Although results obtained from the NSE may be relatively certain for high flows, for studies that aim to inform water resources management with a focus on summer flows, such results should be checked using an alternative model fitting criterion to using only NSE. This could include multi-objective optimisation to identify pareto-optimal solutions.

4. Conclusions

The sources of uncertainty for streamflow simulations vary depending on the flow regime, catchment conditions, choice of model and data employed, along with specific implementation decisions. In this study, rainfall ensembles were input into hydrological model ensembles in order to identify dominant sources of uncertainty in streamflow simulations. Development of the GLM framework showed that the precipitation model is mainly driven by weather types. Teleconnection and weather type indices were shown as important for the inter-annual variability.

We assessed the importance of uncertainty sources between different models and performance assessment criteria in order to characterise and compare the impacts of alternative subjective choices of these quantities. The actual amounts of uncertainty are case specific as they depend on these subjective methodological choices. Uncertainties in streamflow simulations due to rainfall forcings are dominant across all models and catchments in this study, and this is attributed to objective choices in this methodology which resulted in a greater constraint on the identification of parameters, relative to the forcings.

The relative importance of sources of uncertainty depended on the choice of model and the objective function used to select the behavioural parameter sets, with greater proportions of U-parameters in simulations optimised with the NSE criterion. Therefore, uncertainties due to model structure and identification of parameters can be reduced for the season or flow regime of interest through the selection of hydrological model and performance criteria. For all three models in this study, the use of lnNSE resulted in lower and more evenly distributed parameter uncertainties compared to NSE. We recommend that NSE is not used for climate change studies where intra-annual, low or mid-flow predictions are being investigated.

This analysis framework can be further extended to other uncertainty sources including uncertainty from evapotranspiration, and additional selection criteria (e.g. PBIAS, RMSE), and can be used for climate change assessment and regional water quality modelling.

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Appendix A. Short introduction to the Generalised Linear Model (GLM) rainfall simulation framework

The spatial Generalised Linear Model (GLM) method was originally developed in Ireland for generating rainfall sequences conditioned by climate scenarios, based on a flexible but formal statistical framework Chandler and Wheater (Chandler and Wheater, 2002). Developed from Coe and Stern (Coe and Stern, 1982), the method is a two-stage rainfall sequence generator composed of an occurrences model and a gamma distributed amounts model. For the first stage, the occurrences model generates zero/non-zero series based on the wet day probability (p_i) which is conditioned by a logistic regression. For each time step, the precipitation occurrence probability (p_i) is determined by:

$$\ln\left(\frac{p_i}{1-p_i}\right) = x_i^T \beta$$

where $\mathbf{x_i^T}$ is the *i*th day transposed predictor vector which consists of spatiotemporal structures and external driving climate variables (Table 3) and $\boldsymbol{\beta}$ is the logistic regression coefficient vector. The variables of $\mathbf{x}$ for the Occurrence model are variable 1 to 9 in Table 3a. Variable 10 is a fix parameter to decide rainfall day. For the spatial occurrence model, the 11th variable is used to condition inter-site occurrence probability. Detail of the methods and algorithm can be found in Chandler (2015). Overall, the binary dependence structures here are in terms of latent Gaussian variables: specifically, a standard normal random variable Z_{si} is related with site s on day i, and Y_{si} is set to 1 if $Z_{si} > -\Phi^{-1}(p_{si})$ where $\Phi(\bullet)$ is the standard normal distribution function and $p_{si} = P(Y_{si} = \text{Occurrence})$.

In the amounts model, the mean rainfall value of the ith wet day (μ_i) are modelled by the gamma distribution. Using a log link function and a constant shape factor, the mean rainfall value (μ_i) is conditioned by the ith day environmental conditions ($\boldsymbol{\xi}$) and is expressed as:

$$\ln(\mu_i) = \xi_i^T \gamma$$

where $\boldsymbol{\xi_i^T}$ is the *i*th day transposed predictor vector which consists of spatiotemporal structures and external driving climate variables (Table 3) and $\boldsymbol{\gamma}$ is the gamma regression coefficient vector. The variables of $\boldsymbol{\xi}$ for the amounts model are variable 1 to 9 in table 3b. Variable 10 is a fixed parameter for the dispersion of the Gamma distribution. For the spatial amounts model, the 11th variable is used to condition inter-site precipitation amounts. As with the Occurrence model, detail of the methods and algorithm can be found in Chandler (2015). Overall, inter-site dependence is specified via correlations between Anscombe residuals which are approximately normally disturbed (see Yang et al., 2005). By doing this, the multivariate normal distribution can be used to be the only correlation-based dependence structure here.

Generally, the GLM internal structures for the precipitation time series are related to temporal or spatial autocorrelation functions which can be represented by orthogonal bases such as Legendre polynomials (e.g. Yang et al., 2005). For external variables, weather states and teleconnection indices are used to be driving information which cannot be derived from the precipitation time series themselves. Using the Newton-Raphson method, the coefficient vectors ($\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$) are estimated by a maximum likelihood framework, and the predictor significances can be determined by formal statistic tests based on likelihood ratios and deviance (Chandler, 2015). Similar to many spatial analysis techniques such as kriging (Cressie, 2015), the residuals from the GLMs are used for spatial modelling. By using the GLM residuals, autocorrelation effects and nonstationary external driving variables of precipitation are adjusted before the spatial relationships are modelled. As an alternative to the common variogram technique (Cressie, 2015), a correlation ρ(i,j) function is used to model the spatial relationships among the GLM residuals from 31 catchments and it is expressed as:

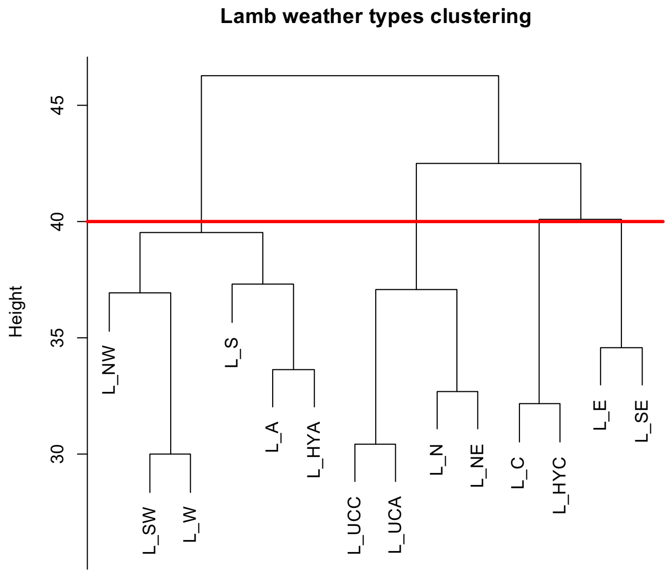
$$\rho(i, j) = \alpha + (1-\alpha)\exp(-\phi d_{ij}^k)$$

where α,ϕ and k are the k-powered decay function parameters, and d_{ij} is the distances between catchments. In general, Chandler and Wheater (2002) considered that the GLM method is a generalised Markov Chain rainfall model. More detail discussion of algorithm can be found in Chun (2011). For formulating GLMs using the above discussed approach, a multisite weather generators which can be executed in R is available from http://www.ucl.ac.uk/~ucakarc/work/glimclim.html. This study result in this paper can be reproduced readily using this R package (Chandler, 2015).

When using the GLM approach, we needed to decide a model structure. In the R package, the rainfall model structures are specified by model definitions (Wheater and Gober, 2013). Similar to Yang et al. (2005), we have identified our rainfall model structure using 7 long precipitation records in Ireland. The reason for using long records to identify our model structure is because we wanted to develop a model which can include more robust climate predictors that can be used in climate change studies in the future. In other words, the GLM structure selection is similar to deciding the number of reservoirs for a hydrological conceptual model. After the model structure was decided, we identified the GLM model parameters for 31 stations between 1996 and 2005. Then, we validate our calibrated model using data from 1990 to 1995. One of main limitations of the two parameter estimation method used in this study is that the occurrence rate and rain amounts are assumed to be independent from each other. However, occurrence rate can be correlated rain amounts. Therefore, this is noted as a limitation of this study and it further investigations using this uncertainty decomposition framework should implement other joint estimation rainfall model schemes for testing different rainfall simulation approaches.

Appendix B. Variable selections

Regarding our variable selection, we admit that it can be subjective for our final selected weather types. We first use cluster analysis to be our exploratory tool to see the relationship between weather types. Like any clustering analysis methods, we need to subjectively pick our threshold (the red line in the figure) or number of clusters. Based on the below cluster analysis results, we decided that we will pick three to five clusters.



Then, for our variables selection, we use factor analysis to have our dimension reduction to three, four and five factors. We use the highest loading weather types to be the represented variables for the identified three to five factors. First, we tried five represented variables (L_N, L_W, L_A, L_C and L_E) for the five factors in our GLMs. However, our fifth weather type (L_E) become insignificant variable in our GLM model. The insignificant results for easterly (L_E) may be its high collinearity to westerly (L_W). Therefore, we use four represented variables of five factors. For three variables, we can still get all significant results in our GLM models. However, using three variables instead of four variables, we will have more information loss. Therefore, we use four representative variables. Since four represented weather types (L_N, L_W, L_A and L_C) only have between 0.54 and 0.87 loadings for each factors, our final explained variance by the four representative weather types is only around 60%. In any case, the used variable selection is subjective. Some other variable selection approach should be developed by further considering how to minimise the loss of information in the predictors.

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