A weather-type conditioned multi-site stochastic rainfall model for the generation of scenarios of climatic variability and change

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Abstract

Further developments of a stochastic rainfall model conditioned by weather types for the water resource region of Yorkshire, UK, are presented. The model is extended to multi-site and a new technique is developed to allow the reproduction of historical monthly rainfall cross-correlation statistics. Monte-Carlo simulation and sampling techniques are combined to preserve monthly historical rainfall cross-correlation between two sub-regional Neyman-Scott Rectangular Pulses (NSRP) rainfall models. These are conditioned seasonally with a semi-Markov weather generator and used to generate multiple long synthetic series for climate impact assessment in Yorkshire, encompassing an area of some 15,000 km^2. An example application of the model in constructing a climate change scenario for 2021-2050 is detailed. Current UK climate change scenarios show change in both airflow patterns and rainfall properties. In climate scenario development it is therefore desirable to be able to change the frequency of weather state occurrence as well as the mean and variance statistics of rainfall. This methodology allows both the impact of variation in the frequency or persistence of weather states *and* changes in internal weather state properties such as increased intensity or proportion of dry days for example to be investigated. This methodology of simulating potential atmospheric circulation changes may provide a valuable tool for the future management of water resource systems and many other hydrological impact applications.

Keywords

Simulated Rainfall, Climatic Changes, Water Resources, Weather, Stochastic Models, Climate Prediction

1. Introduction

Significant shifts in the spatial and temporal distribution of rainfall across northern Europe have been suggested by both GCM (General Circulation Model) future scenario data (Hulme and Jenkins, 1998) and observational evidence (Mayes, 1995). In the UK, there has been a recent clustering of flood events, such as during autumn 2000 (Marsh, 2001), and drought episodes, such as the 1995 Yorkshire drought (Marsh and Turton, 1996). The 1995-96 drought, with an estimated rainfall return period of more than 200 years (Marsh, 1996), caused severe water stress in the Yorkshire region. The drought necessitated the emergency measure of bringing in water by road tanker from outside the region, and was caused by an unusual pattern of persistent easterly weather systems, with rain falling predominantly to the east of the region rather than the normally wetter west (Fowler and Kilsby, 2002*a*). Linking rainfall properties to atmospheric circulation may therefore provide a valuable tool in predicting the hydrological impacts of future climate change.

In climate change studies, the inaccuracies and the coarse scale of GCM information has led many researchers to adopt synoptic-scale approaches (McGuffie *et al*., 1999). Statistical downscaling approaches have been developed that assume a close link between atmospheric circulation patterns and local climate variables such as rainfall. These linkages have been made for both large and small regions by, for example, Bardossy and Plate (1992), Corte-Real *et al*. (1998), Conway *et al*. (1996) and Fowler *et al.* (2000).

In Fowler *et al.* (2000), three single-site rainfall models were developed for the Yorkshire Water resource region, UK, which covers an area of some 15,000 km^2. Each single-site model represented a climatological sub-region within Yorkshire determined from the analysis of 150 daily rainfall records. This methodology coupled a semi-Markov based weather generator to the Neyman Scott Rectangular Pulses (NSRP) stochastic rainfall model (Cowpertwait *et al.*, 1996a,b) and was conditioned on historical daily rainfall data. Using the climatology of the region, the Lamb weather types (Lamb, 1972; Jenkinson and Collinson, 1977) were grouped into three clusters or weather 'states': 'anticyclonics', 'northerlies' and 'westerlies' (see Table 1), using the same grouping for each sub-region (site). These were then split seasonally (October-April, May-September); giving the winter-anticyclonic (WA), winter-northerly (WN), winter-westerly (WW), summer-anticyclonic (SA), summer-northerly (SN) and summer-westerly (SW) weather states. The weather generator was then calibrated using Lamb's daily weather-type data from 1961 to 1990 and a NSRP model fitted for each weather state. If the weather type for a particular day is unclassified by Lamb (1972), then the weather type is considered to be the same as the previous day. Each combined model produced synthetic time series that reproduce key aspects of the historic rainfall regime down to an hourly time-step at a single site.

This paper presents the further development of this modelling methodology to allow multi-site generation of synthetic rainfall series for climate change impact assessment. The modelling of spatial-temporal rainfall based on stochastic point processes goes as far back as Le Cam (1961), with the approach developing rapidly in the 1980s (e.g. Waymire et al., 1984; Cox and Isham, 1988). More recently, multi-site rainfall generation has been demonstrated by many authors (Wilks, 1998; 1999; Wilks and Wilby, 1999; Srikanthan and McMahon, 2001), with most using a Markov chain process to simulate rainfall occurrence as a function of observed or modelled synoptic scale variables (e.g. Hughes and Guttorp, 1999; Bellone *et al*., 2000; Palutikof *et al*., 2002; Charles *et al*., 1999; 2003). Downscaling techniques have since been further developed for multi-site precipitation generation using broad atmospheric circulation patterns by many authors (e.g. Corte-Real *et al.* 1999a,b; Bellone *et al*., 2000; Bardossy *et al*., 2001; Qian *et al*., 2002; Wilby *et al*., 2002; 2003).

In the current study, Monte-Carlo simulation and sampling techniques are combined to produce long synthetic rainfall series at multiple sites within sub-regions with very different rainfall properties arising from the same weather state. The coupling of a weather generator to a multi-site stochastic rainfall model is extremely powerful as it permits investigation into the impacts of both variations in weather type persistence or frequency *and* internal weather type properties such as rainfall intensity changes (e.g. Osborn, 2000; Fowler and Kilsby, 2003a,b). Here, the model is calibrated to simulate rainfall for the UKCIP98 2021-2050 climate change scenario (Hulme and Jenkins, 1998) using variations in both weather type occurrence and rainfall properties. Using this, and other climatic variability and change scenarios based on UKCIP98, the impact of future climate change upon the Yorkshire water resource system was investigated by Fowler *et al*. (2003). However, it is possible to use the same methodology to examine the impacts of the new UKCIP02 scenarios (Hulme *et al*., 2002) or indeed any other climate change scenario. This technique may provide a valuable tool for future water resource management, as well as other hydrological applications, as climatic trends, both observed and modelled, can be readily translated into hydrological impacts.

2. Background

In Yorkshire, annual rainfall varies from just 600 mm in the eastern lowlands (Vale of York), to over 2000 mm at high western sites (Pennines). The main rainfall source is weather systems from the westerly quadrant, and this has resulted in the installation of supply reservoirs, predominantly in the Pennine west of the region. These fill during winter months and are drawn down in summer months, with relatively little carry-over from one year to the next. The 1995-1996 drought was caused by an unusually high number of easterly weather systems during the summer and autumn months of 1995, followed by a highly anticyclonic winter through to 1996 (Fowler and Kilsby, 2002*a*). This resulted in a water deficit in the west of the water resource region, the normal source of the majority of the population’s water supplies. The current climatic trends in Yorkshire (Fowler and Kilsby, 2002*b*) and the future projection of climate change in the UK in general (Hulme and Jenkins, 1998) suggest that winters will become wetter and summers drier on average. The relative changes in rainfall will be largest in the south and east of the UK, with summer reductions and winter increases as high as 50 and 30 percent respectively by the 2080s under the highest emissions scenarios (Hulme and Jenkins, 1998).

This exacerbation of seasonal rainfall contrasts in a changing climate may have a profound effect on water resource systems in already vulnerable areas, such as Yorkshire. In much of the north of England, short-term summer drought can have an extremely detrimental effect on water supplies. The geology of many areas results in little, if any, groundwater storage potential, with a resulting reliance upon surface water resources. These resources, particularly single-season reservoirs, can be depleted rapidly during a dry period, initiating a water resource 'drought'. Northern regions are therefore much more likely to suffer single-season droughts, whereas groundwater dominated catchments in the south require multi-season droughts to seriously affect water supplies. The projected climate changes may therefore impact water supplies in northern regions such as Yorkshire more dramatically than in southern regions of the UK which have more groundwater resources. Establishing the likely effect of such climate changes upon the reliability, resilience and vulnerability of water resource systems (e.g. Hashimoto *et al*., 1982*a,b*; Fowler *et al*., 2003) has become a priority for the successful future management of such resources.

In England and Wales, water companies have generally used the 'factor' approach to produce estimates of the reliability of their water supplies under a climate change scenario. This method simply uses a factor taken from the results of a GCM experiment to perturb the mean of a historical rainfall series which is then inputted into a water resource model. This results in no change to the temporal and spatial structure of rainfall fields and is, as such, an unrealistic simulation of climate change. In Fowler *et al*. (2000), a stochastic single-site weather-conditioned NSRP rainfall model was developed for each of three sub-regions within Yorkshire, the split based on the climatology of the region (Figure 1). Each model allowed the generation of long synthetic daily rainfall series, preserving the statistical properties of the calibration series but also enabling the user to change both the rainfall statistics of a weather type and its frequency of occurrence. Unfortunately, however, each model generated rainfall only at a single-site level. The further development of this methodology to allow multi-site modelling will allow its use in climate change impact studies and answer basic questions such as that of water resource reliability.

3. Model development

3.1 The spatial NSRP model

The NSRP model is a clustered point-process stochastic rainfall model, and is fully described by Cowpertwait (1991; 1994; 1995) and Cowpertwait *et al.* (1996*a*,*b*). The spatial NSRP model was originally developed from a single site rainfall model and was intended to accurately represent the statistics of several sites simultaneously and with spatial consistency. The multi-site model first generates a uniform spatial-temporal NSRP model (following Cowpertwait, 1995) with uniform expected mean and variance of daily rainfall (or other chosen time period), probability of a dry period, spatial cross-correlation with distance, and autocorrelation properties. A scale factor is then applied to the time series of each site (here on a weather state basis). Whilst this procedure allows for a spatially varying mean and variance, albeit with a uniform standard error, the autocorrelation and dry period probabilities remain uniform.

The six parameters of the spatial NSRP model can be found in Table 2. These are the same as the single-site model, with the exception that ν (the mean number of rain cells associated with a storm origin) in the point model is replaced by ρ (the mean cell density associated with a storm origin) and γ (the cell radius parameter). The stochastic process at a point within the spatial model is equivalent to a single-site model at that point, provided these parameters are related by:

$$\nu = \frac{2\pi\rho}{\gamma^2} \tag{1}$$

In the spatial model, $\mu_m(1)$ (mean hourly rainfall) is used to estimate the scaling factor, φ_m, for each site m. This is equivalent to dividing each hourly series by its mean to produce n

transformed series. Each series then has the same mean and approximately the same variance (i.e. approximate uniformity in space). The model parameters are estimated by using a simplex algorithm to minimise the following sum of squares:

$$\sum_{m=1}^{n} \sum_{f_m \in F} \omega(\hat{f}_m)\{1 - f_m / \hat{f}_m\}^2 \tag{2}$$

subject to: λ, β, ν, η, ξ, γ> 0, where f_m is the estimated statistic calculated to result from a chosen set of parameters for site *m*, $\hat{f}_m$ is a sample estimate of the statistics taken from the hourly data for the *m*th site, and *F* denotes a set of aggregated single-site properties. The $\omega(\hat{f}_m)$ are weights that can be applied if some of the properties are to be given greater importance in the fitting procedure (Cowpertwait, 1995).

3.2 Model limitations and regionalisation

As mentioned above, a limitation of the NSRP spatial model is that the dry period probability is uniform in space. However, the assumption of uniformity is only a reasonable approximation in small regions and is certainly not valid where rainfall varies significantly with orography. The dry day probability (or proportion of dry days (PD)) is highly variable between the western and eastern sub-regions for the same weather state (see Fowler *et al*., 2000). This means that separate NSRP models must be calibrated for each sub-region and a technique developed to preserve spatial cross-correlation properties between the separate sub-regional models.

The historical spatial cross-correlation for annual and monthly rainfall totals from 1961-1990 in the three sub-regions (represented by indicative sites at Moorland Cottage, Lockwood Reservoir and Kirk Bramwith) are shown in Table 3. Since weather states in the south-eastern and north-eastern sub-regions share similar spatial cross-correlation and PD properties it was decided to simplify the modelling procedure by amalgamating the two areas into a new 'eastern' sub-region. Weather states in the 'eastern' sub-region therefore derive their seasonality from the model previously fitted to Lockwood Reservoir in Fowler *et al.* (2000), splitting the climatological year into two intervals, January to June (season 1) and July to December (season 2). Season 1 and season 2 are arbitrarily titled 'summer' and 'winter' in this case. In the 'western' model, the weather state seasonality is taken from the Moorland Cottage model detailed in Fowler *et al*. (2000), with 'summer' from April to August and 'winter' from September to March. In both cases, the choice of seasons was derived objectively by k-means clustering, a technique to group data into minimum variance groups. A series of Monte-Carlo simulations additionally showed that parameterisation by month was unnecessary, and that the use of all of Lamb's 27 weather types (Lamb, 1972) separately provided no additional benefit for this case.

To determine whether accurate spatial cross-correlation properties can be retained between the two sub-regional models, Monte-Carlo simulation was used to produce an ensemble of fifty realizations of the 1961 to 1990 period for each sub-region using the models developed by Fowler *et al*. (2000). The results suggested that the annual and monthly historical spatial cross-correlation between sub-regions can be synthetically reproduced by the model within the fifty sequences. This is developed in more depth later in the paper.

3.3 Model calibration

Concatenated rainfall series were produced for each 'summer' and 'winter' weather state for each site in the eastern and western models respectively. A spatial NSRP model was then fitted for each weather state for each of the western and eastern sub-regions using 28 daily rainfall records from 1961-1990. This involved the fitting of 19 sites within the western region and 9 sites within the eastern region (see Figure 1). These particular rainfall series were chosen as they provide the necessary input data for reservoir and river resources within the Yorkshire water resource model (see Fowler *et al*., 2003). Site details can be found in Tables 4 and 5 for the western and eastern regions respectively.

The model was fitted using the following sample statistics, where *i* denotes an index site representative of the sub-region, for the western model, Moorland Cottage, and for the eastern model, Osmotherly Filters, and *k* denotes a spatial average: $\mu_i(24)$ (24-hr mean rainfall), $\phi_k(24)$ (24-hr dry period probability) where a dry day is defined as having less than 0.2 mm rainfall, $V_i(24)$ (variance of 24-hr rainfall amounts), $V_i(48)$ and all possible 24-hr cross-correlations, where cross-correlation denotes a correlation between two different sites. Auto-correlation, a lagged correlation in time at the same site, was not used in fitting as this is reproduced by the weather state generator by the preservation of historical weather state persistence probabilities (as shown in Fowler *et al*., 2000). The PD statistic used is a spatial average across the sub-region for a particular weather state, as the NSRP model is unable to produce spatially varying PD. Weights were assigned to sample moments during the fitting procedure to improve the model fit; $\mu_i(24)$ was given a weighting of 10, $\phi_k(24)$ a weighting of 3, $V_i(24)$ and $V_i(48)$ were assigned a default unit weight. The 24-hr cross-correlations were given a weighting of 5. The fitted parameters for the six weather states in the eastern and western model can be found in Table 5.

After fitting, the parameters were validated using a Monte-Carlo process. An ensemble of 50 simulations of the same length as the concatenated series was generated for each weather state. This gave uncertainty bounds (the 5th and 95th percentiles from the 50 simulations) about the simulated daily spatial cross-correlation, the most important aspect of a spatial rainfall model, and a measure of fit of the other simulated statistics.

The observed, fitted and simulated statistics at the western model index site of Moorland Cottage are in Table 4(a). The model fitted values and simulated values provide a good match to observed statistics, although variance is generally slightly underestimated. In the main, site statistics are reproduced for each of the six weather states within the western model. The $\mu(24)$ statistic is accurately simulated. The $\phi(24)$ statistic is also well simulated, for most weather states within two percent of the areal average historical $\phi(24)$. However, the daily variance is underestimated by the model for all weather states. This may be a consequence of the assumption of a uniform standard error inherent in the spatial NSRP model. The underestimation of variability by stochastic rainfall models is further discussed in Katz and Parlange (1998). Daily cross-correlations are well preserved by the western NSRP model (Figure 2). It can be seen that many of the observed daily cross-correlations for the winter weather states, particularly the westerly state, lie outside the 5 and 95 percentiles of the simulated series. This can be explained by the high rainfall variability of the winter westerly weather state, which is greatly dependent upon altitude and westerliness in the Pennines. This highlights a deficiency in the spatial NSRP model, in that the model fits a single curve to spatial correlation with distance, and does not address variability in this parameter.

The observed, fitted and simulated statistics for the eastern model index site at Osmotherly Filters are in Table 4(b). The simulated statistics are very similar to the observed statistics, excepting a slight reduction in variance and increase in PD within the simulated series. The daily cross-correlations fitted by the model can be seen in Figure 3. The daily cross-correlations between sites are well matched by the model simulations for all six weather states.

3.4 Model validation

For model validation, a 1000-yr weather state series was generated using the semi-Markov chain model described in Fowler *et al*. (2000), based on observed data from the period 1961-1990. This weather state series (adjusted for site seasonality using the same seasons as described in section 3.2) was then used as input to the eastern and western spatial NSRP models, producing 28 rainfall series. These simulated daily rainfall series from the NSRP models were then aggregated to monthly and compared with monthly rainfall values that would be expected, given that particular sequence of weather states.

Figure 4 shows that, for the eastern model, simulated statistics at three example sites of Lockwood Reservoir, Wykeham Nursery and Birdsall House provide a good match to expected mean monthly rainfall amounts. The remaining six sites simulated using the eastern model also show a close correspondence to the expected mean monthly rainfall (not shown). The mean annual expected and simulated rainfall totals are also closely matched.

In the western spatial NSRP model, simulated annual rainfall is overestimated at some sites. This is due to a large disparity in the average rainfall production of different weather states within the model. In particular, the winter westerly weather state produces twice as much rainfall as any other weather state. This can cause increased winter rainfall at sites with a low annual rainfall total such as Brignall (Figure 5). Switching between weather types on a daily basis introduces a time lag between weather state initiation and generation of rain cells associated with that weather state. This occurs due to the disparity in scale between the effective length of storms (several days) and the applied scale factors (a single day). This may normally cause small anomalies in the rainfall rescaling process. However, in the case of the western NSRP model, due to the very wet nature of the winter westerly weather state when compared to other weather states, a significant discrepancy occurs. This produces a bias during the winter season that increases the rainfall and requires a consequent correction to ensure that the expected annual rainfall amounts are obtained at each site. This is further explained in Fowler et al. (2000).

3.5 Preserving spatial cross-correlation properties between sub-regional models

For the model to be used in a water resource study it is necessary to reproduce the spatial cross-correlation properties between the two sub-regions. If the same weather state series is used as input to the two, otherwise independent, models it would be expected that this would result in a degree of spatial cross-correlation. However, this is limited by the stochastic nature of the NSRP model where a wide range of rainfall amounts are equally likely to be associated with the same weather state. This is shown in Figure 6 for Moorland Cottage and Lockwood Reservoir and means that the stochastic model series cannot be expected to reproduce one-to-one correspondence of rainfall amounts to observed weather states. Rather, the average statistical properties of the weather states are reproduced, with a limited correspondence due to the use of the same weather state series.

A sampling methodology was therefore considered necessary to match the pair of simulated time series that best reproduce the observed spatial cross-correlation. As before, a single 1000-yr weather state series was generated using the semi-Markov chain model detailed in Fowler *et al.* (2000), based on observed data from the period 1961-1990. The weather state series was adjusted by site seasonality for the eastern and western NSRP models. Fifty 1000-yr daily simulations of rainfall were then generated for each of the eastern and western sites, using the same weather state series as input for each. These were totalled to give monthly rainfall series. The spatial cross-correlation between the eastern and western monthly rainfall series was then determined for each pairing of the fifty simulated series, giving 2500 possible cross-correlations between Moorland Cottage and Lockwood Reservoir.

To reproduce the historical spatial cross-correlation between the simulated series it proved necessary to divide them into shorter sections. In this procedure, there is a trade-off between the preservation of monthly spatial cross-correlation properties and the reproduction of accurate daily rainfall statistics over the 1000-yr series. This is illustrated by Figure 7 where a 10-yr section enables the reproduction of a higher monthly spatial cross-correlation statistic than a 50-yr section for example. To ensure coherence with historical records however, a section length must be chosen that does not compromise the model's reproduction of average observed daily rainfall statistics, therefore maximising the length of section while still preserving the historical monthly rainfall cross-correlation between Moorland Cottage and Lockwood Reservoir (see Table 3). A section length of 50-years was found able to produce a spatial cross-correlation statistic of 0.2 between Moorland Cottage and Lockwood Reservoir without biasing the average daily rainfall statistics. This was checked by the evaluation of mean statistics for each paired 50-year section of the 1000-year series at each of the two sites, although a bootstrap procedure could also have been used to establish confidence intervals. The use of shorter time-periods, particularly less than that of the 30-year calibration period, may compromise the model, as years with a greater proportion of dry days may show a higher spatial cross-correlation.

Therefore, for each 50-yr section, eastern and western model simulations were paired from the 2500 possible combinations. These were chosen objectively to best preserve the historical monthly cross-correlation statistic between the two sites. These twenty 50-yr sections were then reconnected to produce a single 1000-yr daily rainfall series for each of the 19 sites in the western model and the 9 sites in the eastern model.

The benefit of using this modelling methodology rather than a simple re-sampling approach was investigated. For each of Moorland Cottage and Lockwood Reservoir the historical daily rainfall series from 1961-1990 was concatenated into bins according to the observed daily weather states of SA, SN, SW, WA, WN and WW. A rainfall amount frequency relationship was determined for each of the six weather states (see Figure 6). A re-sampling approach with replacement was then used to generate 100 30-year synthetic daily rainfall series for each site by using the historical 1961-1990 weather state series as a template. On a WW day for example, a particular rainfall amount is randomly selected from the WW bin. This methodology was used to construct a daily rainfall series, giving 100 realisations for each site of the 1961-1990 period. These synthetic daily series were then totalled to give monthly values and the spatial cross-correlation properties analysed.

Results indicate that the methodology of using the NSRP models and then sampling the daily rainfall data in sections to produce 1000-year rainfall series (hereafter called NSRP + sampling) offers some improvement on the simple re-sampling approach (Table 6). The mean cross-correlation of a 30-year section using NSRP + sampling is increased significantly when compared to the re-sampling approach. The maximum and minimum cross-correlation is also increased. The historical spatial cross-correlation of 0.21 can be reproduced by this approach within the 100 test simulations.

The use of the NSRP + sampling methodology is justified by the improvement in correlation statistics as well as by two additional factors. The first of these is the ability to produce rainfall amounts and structures using statistical distributions. This allows the generation of synthetic rainfall series with a different temporal and spatial structure to existing historical data. The second is the capability to modify the model for future climate cases by changing the statistical properties of a weather state rather than relying on a 'factor' modification that results in no change to the temporal and spatial structure of rainfall fields. As this procedure preserves the cross-correlation properties and average rainfall statistics for the whole of the Yorkshire region it will be suitable for a wide range of hydrological impact studies.

4. Using the model to construct a climate change scenario

This section is used to illustrate how the modelling methodology described above can be used to generate synthetic rainfall time series for climate change impact studies.

The UKCIP98 climate change scenarios (Hulme and Jenkins, 1998) were constructed using the HadCM2 GCM output. These scenarios are based upon the HadCM2 experiments that use a one percent rise per annum in greenhouse gas concentrations over the next century; similar to the IS92a emissions scenario (Leggett *et al.*, 1992). Four scenarios are presented: Low, Medium-Low, Medium-High and High. The Medium-High scenario provides detail on more climatic variables than the other three scenarios, and for this reason has generally been used for climate change impact assessments. In this analysis, a climate change scenario from 2021-2050 will be considered. Four grid-cells cover the UK. The Yorkshire region lies equally in the northern England grid-square and the south-eastern England grid-square. It is assumed, therefore, that rainfall change in Yorkshire will be the mean of the two grid-squares for each scenario.

Changes to mean rainfall amount and rainfall variability for summer and winter, defined as April to September and October to March respectively, for the 2021-2050 climate change scenario (Hulme and Jenkins, 1998) are shown in Table 7.

Seasonal change in airflow characteristics over the British Isles under the UKCIP98 Medium-High scenario are also assessed by Hulme and Jenkins (1998). Their analysis suggests a reduction of northerly and easterly flow in autumn, decreased westerly and north-westerly flows and increased anticyclonicity in summer, and decreased anticyclonicity in winter and spring. This suggests that any increase in winter rainfall will come from an increase in westerly flows combined with an increase in mean daily rainfall on a westerly day. In summer months, the reduction in rainfall may be an outcome of an increase in anticyclonic conditions combined with a reduction in westerly mean daily rainfall.

These changes in airflow characteristics are similar to those of the high-phase North Atlantic Oscillation (NAO). The NAO index (Jones *et al*., 1997) is the difference in the normalised sea level pressure over the Azores and Iceland and is a measure of the strength of westerlies across the UK. A useful winter index is given by the December to March average of the pressure difference. In Fowler and Kilsby (2002*b*), it was shown that rainfall in Yorkshire is affected by the phase of the NAO. During a positive or high-phase winter-NAO period, such as from 1980-1990, there is an increased frequency of the WW and SA weather states, to the detriment of the SW and WA weather states. This causes increased winter rainfall and decreased summer rainfall simply as a function of change in weather type frequencies (Fowler *et al*., 2000).

This can be quantified by a very simple example. A 1000-yr daily weather state series was fitted on the period from 1980-1990 (mean NAO of 0.84) and again for 1961-1990 (mean NAO of 0.27) simulating a high-phase NAO and the baseline respectively, although it must be noted that the differences in the mean NAO between the two periods are not statistically significant. A 1000-yr daily rainfall series was then produced for every site for each of the high-phase NAO and baseline simulations. During a high-phase NAO there is an increase in winter rainfall of two percent in the west and one percent in the east. This is offset by a slight reduction of one percent in summer rainfall in the west, but no change is observed in the east. These changes can be seen in Table 8.

Therefore a historic analogue, the high-phase NAO weather state series, was used to simulate realistic change in airflow characteristics for the 2021-2050 climate change scenario. This uses NAO conditioning to create an analogue of the UKCIP98 scenarios rather than using GCM output directly to drive the Markov model. Further change in mean rainfall amount and variability necessary to match the changes projected under the UKCIP98 Medium-High scenario was applied by the refitting of the SW and WW weather states for the eastern and western NSRP model, taking into account the changes to mean rainfall already achieved by the use of the high-phase NAO scenario rather than the baseline (see Table 8). These precipitation changes will only reflect changes in atmospheric circulation, and forcing by atmospheric humidity may not be captured. The new statistics for $\mu(24)$ and $V(24)$ for the SW and WW weather states are presented in Table 9. The model was then recalibrated using these statistics. The new fitted parameters for the 2021-50 climate change scenario are in Table 10. These parameters provide accurate statistics at sites within the eastern and western NSRP models, simulating the rainfall changes of the UKCIP 2021-2050 climate change scenario. The methodology using Monte-Carlo simulation and sampling techniques detailed in section

3.5 must then be followed to produce a synthetic daily rainfall series for each of the 28 sites using the new parameter set. When inputted to a model of the Yorkshire Grid, this will then allow the impacts of the UKCIP98 2021-2050 climate change scenario on water resources in Yorkshire to be reliably assessed. This modelling approach was used by Fowler et al. (2003) to examine the effects of climatic change, including the scenario detailed here, and variability upon the reliability, resilience and vulnerability of water resources in Yorkshire, UK.

5. Discussion and conclusions

This paper presents the further development of a multi-site stochastic rainfall model for climate impact assessment in the Yorkshire region, UK, in response to recent concern about the estimation of reliability of regional water resource systems under future climate change scenarios. This model improves upon the 'factor' approach previously adopted in the UK water industry where observed rainfall records are simply modified by a factor change to the mean derived from GCM simulations, resulting in no changes to the temporal structure of rainfall fields. The approach described here uses series of weather types to provide the temporal sequence and high time-aggregation behaviour, and the NSRP model to reproduce hourly and daily statistics of rainfall. This offers considerable improvement upon the simple re-sampling of historical data and thus demonstrates that the additional complexity of the methodology is warranted. The methodology allows the results of GCMs to be used directly, via analyzed GCM Lamb weather types, or indirectly, as trends in both weather-state and rainfall characteristics can be extracted and interpreted within the model.

The methodology is also easily transferable to other regions, particularly within the UK, and can provide synthetic rainfall data down to the hourly level, making it suitable for more detailed impact studies such as variation in river flows and flood risk estimation. Within other regions of the UK it would be necessary to repeat the identification of homogenous sub-regions and to identify suitable groupings of Lamb weather types. Outside the UK, other objective circulation classification schemes would be needed to identify weather states. It should also be noted that outside the North Atlantic region the NAO should not be used as a historic analogue for future climate change.

To use the modelling methodology for climate impact studies, it was necessary to make a number of implicit assumptions about future rainfall and it is useful to summarize these here. It is assumed that change in future rainfall properties may be represented by a combination of change in future circulation patterns and change in the daily rainfall statistics of these circulation types. Here, a historic analogue is used to represent change in future circulation patterns, provided by an observed high-phase NAO time series, and change in daily rainfall statistics is provided by the refitting of the mean and variance statistics of the SW and WW weather states only. For other weather states, the modelling approach implicitly assumes that the statistical properties of the observed 1961-1990 data will remain valid for the future climate scenario: similar weather types imply similar rainfall in the future. This assumption includes spatial cross correlation properties within the sub-regions, and the continued homogeneity of sub-regions under future climate. Additionally, the spatial cross correlation of monthly rainfall between the sub-regions, which is not dependent on weather types, is assumed to remain constant under future climate change.

There are a few caveats to the approach of using weather types in model conditioning, as detailed by Wilby (1997). Firstly, as atmospheric circulation is essentially dynamic, it is arbitrary to define daily weather types, even when very clearly defined criteria are applied. Moreover, on some days regional airflows are apparent that make the assignment of a single weather type for the whole of the UK infeasible (Mayes, 1991). However, perhaps the most serious hindrance to using weather types in a downscaling methodology is that the relationship between a weather type and rainfall properties is itself constantly changing. This is shown in Fowler and Kilsby (2002b) for the case of the high- and low-phase winter North Atlantic Oscillation index, for example.

A number of other important issues are raised in this paper about constraints upon the stochastic representation of distributed rainfall imposed by the NSRP multi-site stochastic rainfall model. The model was originally developed from a single site rainfall model and intended to accurately represent the statistics of several sites simultaneously with spatial consistency. To achieve this the multi-site stochastic model first generates a uniform spatial-temporal NSRP model (following Cowpertwait, 1995) with uniform expected mean and variance of daily rainfall (or other time interval), probability of a dry period, spatial cross-correlation with distance, and autocorrelation properties. A scale factor is then applied to the time series of each site, here on a weather state basis. Whilst this procedure allows for a spatially varying mean and variance, albeit with a uniform standard error, the correlation and dry period probabilities remain uniform. However, the assumption of uniformity of dry period probabilities is only a reasonable approximation in small regions and certainly not valid where rainfall varies significantly with orography such as in the Yorkshire region. A methodology such as that described in this paper is therefore necessary to ensure spatial consistency until the multi-site NSRP model is further developed to allow physically realistic simulations of spatially varying PD. Such development should also assess the assumptions of uniform spatial- and autocorrelations.

From a time scale perspective, it is important to consider how well the methodology would be expected to perform in terms of variability across the hydrologically useful time aggregation scales when fitted to daily and 48-hr statistics. The multi-site NSRP model contains representations of rain cells (tens of minutes duration), storms (tens of hours duration), weather type persistence (days duration) and seasonality (of six months duration). For aggregation periods of less than 1 day we would not expect a good representation of observed variability. However, at daily or weekly aggregations we would expect a better representation of variability as these periods reflect the structure of the stochastic model and the calibration statistics. At a monthly aggregation period and upwards, we would expect to find a significant underestimate in the variability, although this is mitigated slightly at the 6 month aggregation level by the representation of seasonality. These issues go far beyond the scope of this paper however, in which statistics of a daily resolution are mainly considered. At the longer end of the time spectrum, representation of seasonal, inter-annual or inter-decadal climatic variability within synthetic rainfall models remains the subject of ongoing research. Such issues become relevant to the scope of this paper when it is considered that a water resources model may effectively accumulate rainfall totals over periods exceeding a week. In such cases it is considered that the observed variability of the water resource system under study may exceed that estimated by simulation.

The methodology presented here constitutes an improvement upon current RCM generated rainfall as it can produce unlimited synthetic sequences of rainfall at an hourly level and provide realistic variation in both weather type occurrence and associated rainfall amount. It is recognised, however, that alternative approaches are necessary to accurately represent inter-annual and decadal scale climate variability and that this approach may therefore be more suited to other climate change impact applications such as urban drainage, flash flooding and catchment-scale studies.

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List of figures

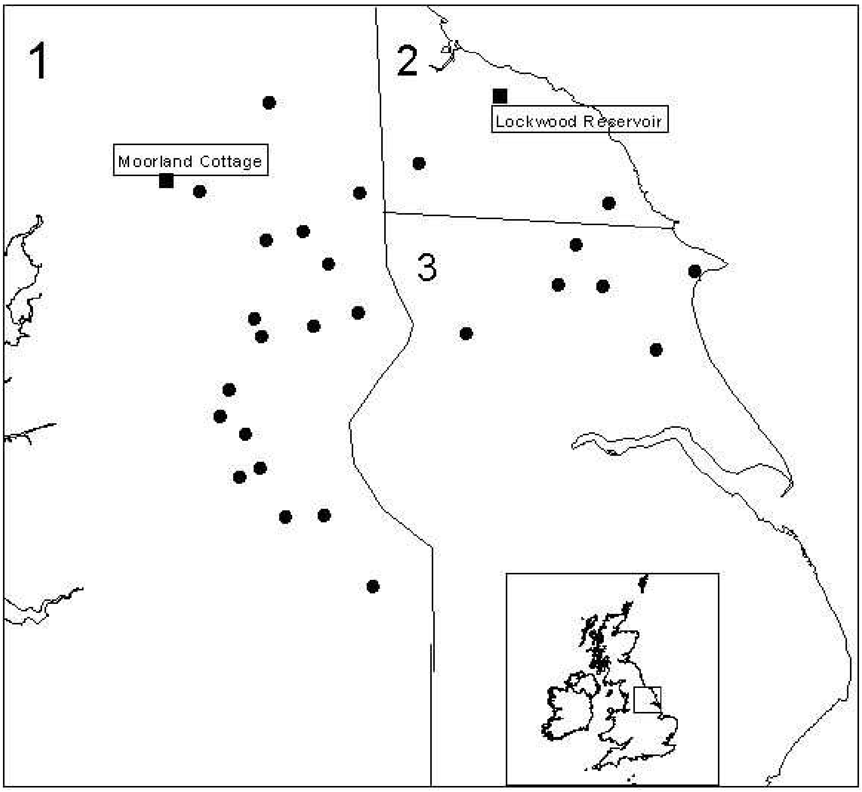

Figure 1. The three Yorkshire precipitation sub-regions developed in Fowler *et al*. (2000). Here, sub-regions 2 and 3 are amalgamated to form an 'eastern' sub-region but sub-region 1 is kept intact to form a 'western' sub-region. Rain gauges used in the study are indicated by black circles and the two representative sites, Moorland Cottage and Lockwood Reservoir, are indicated by black squares.

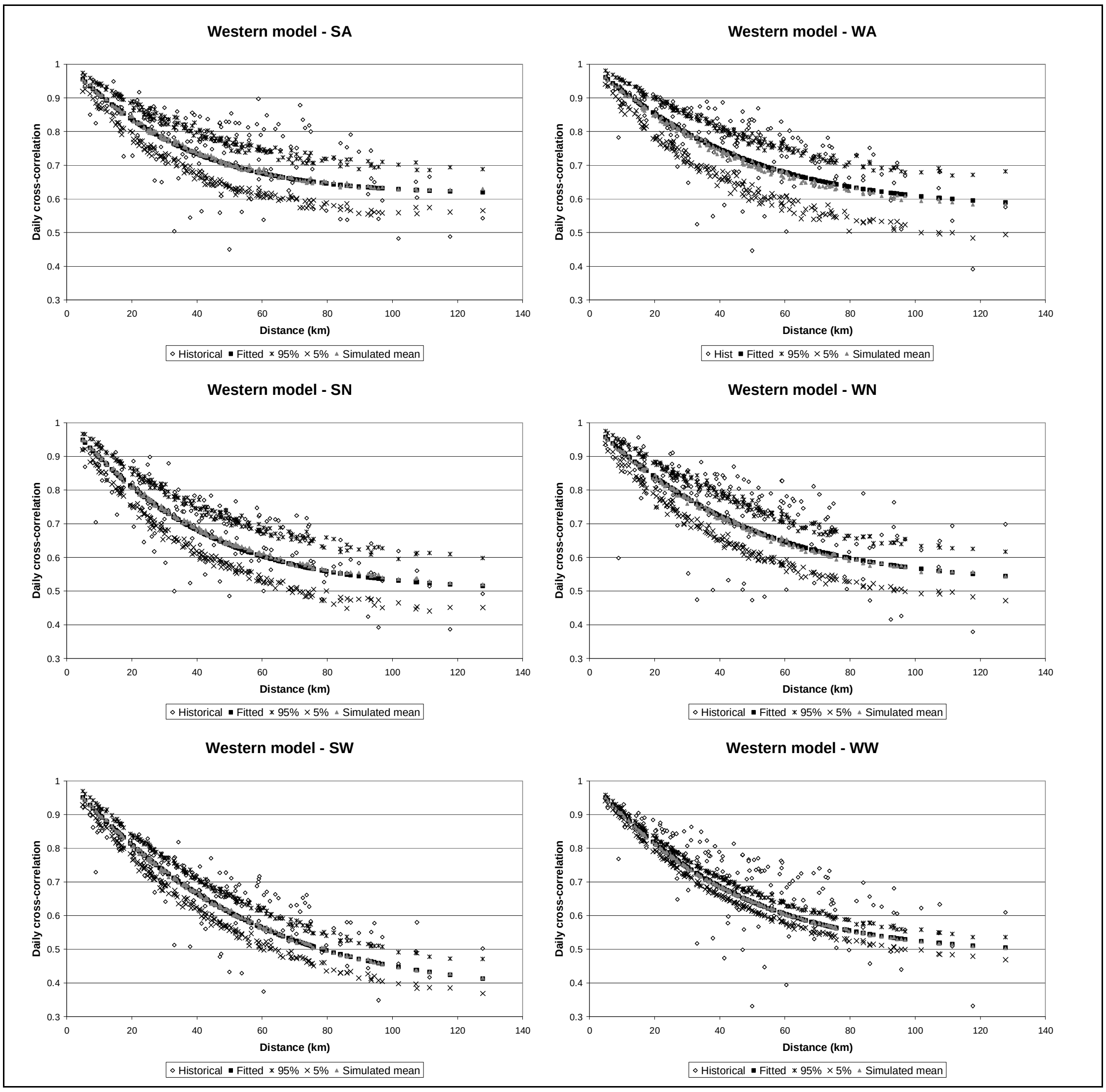

Figure 2. Daily spatial cross-correlations: observed, fitted, simulated with 95 and 5 percentiles from 50 simulations for the western model weather states.

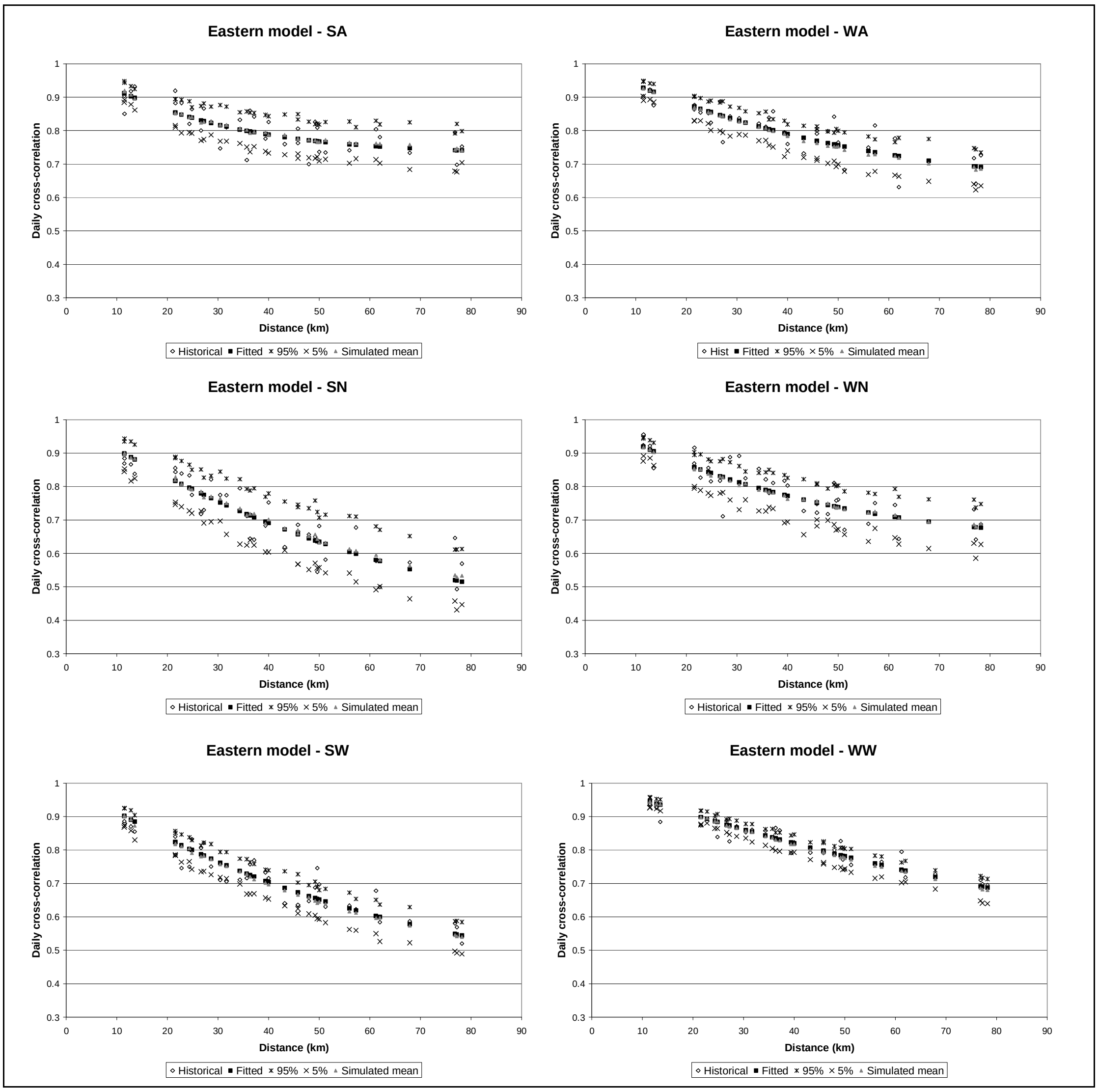

Figure 3. Daily spatial cross-correlations: observed, fitted, simulated with 95 and 5 percentiles from 50 simulations for the eastern model weather states.

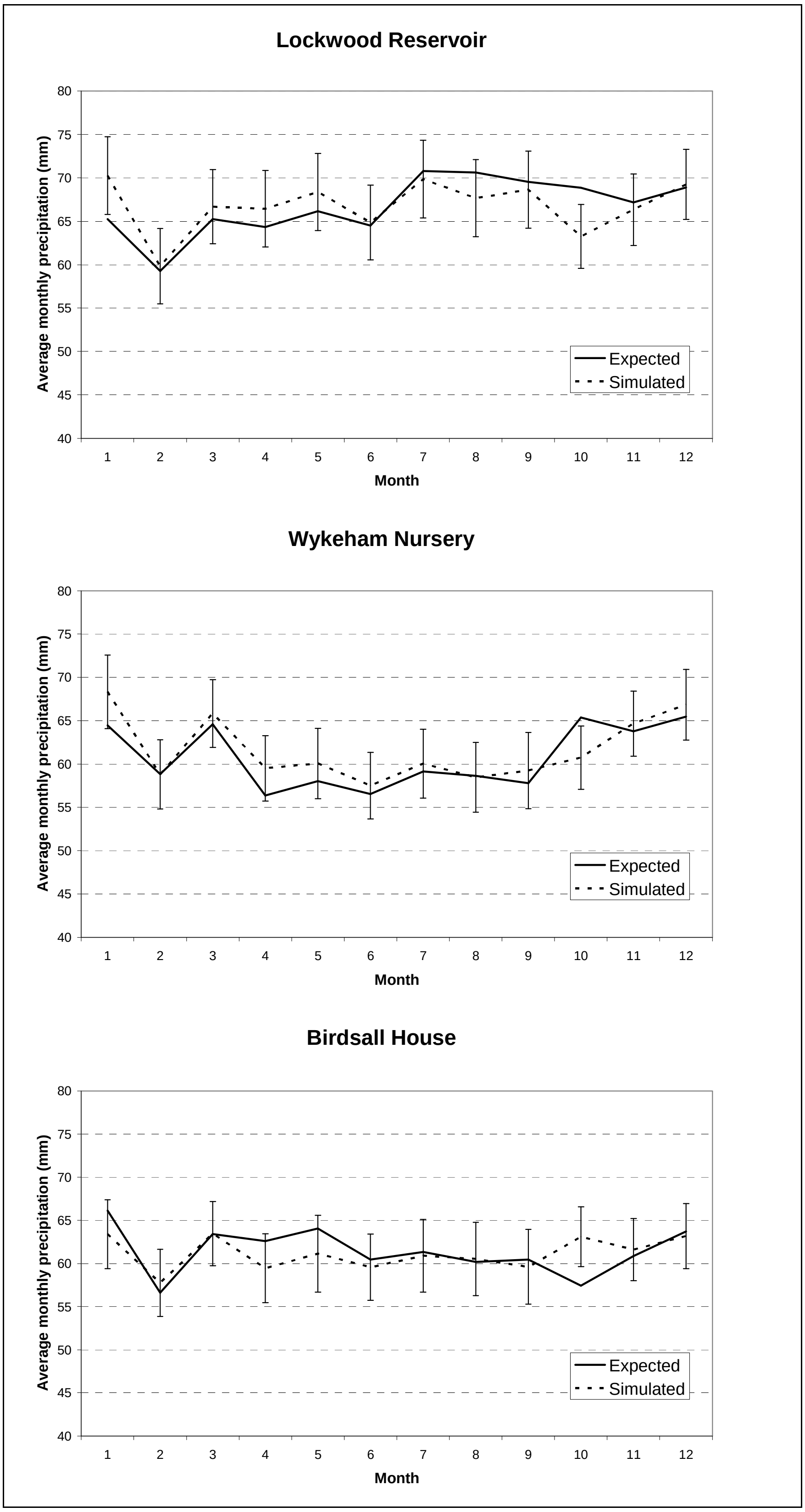

Figure 4. Comparison of expected and simulated monthly mean precipitation (mm) at Lockwood Reservoir, Wykeham Nursery and Birdsall House (eastern spatial NSRP model). One standard deviation either side of the mean is illustrated to show significance of differences.

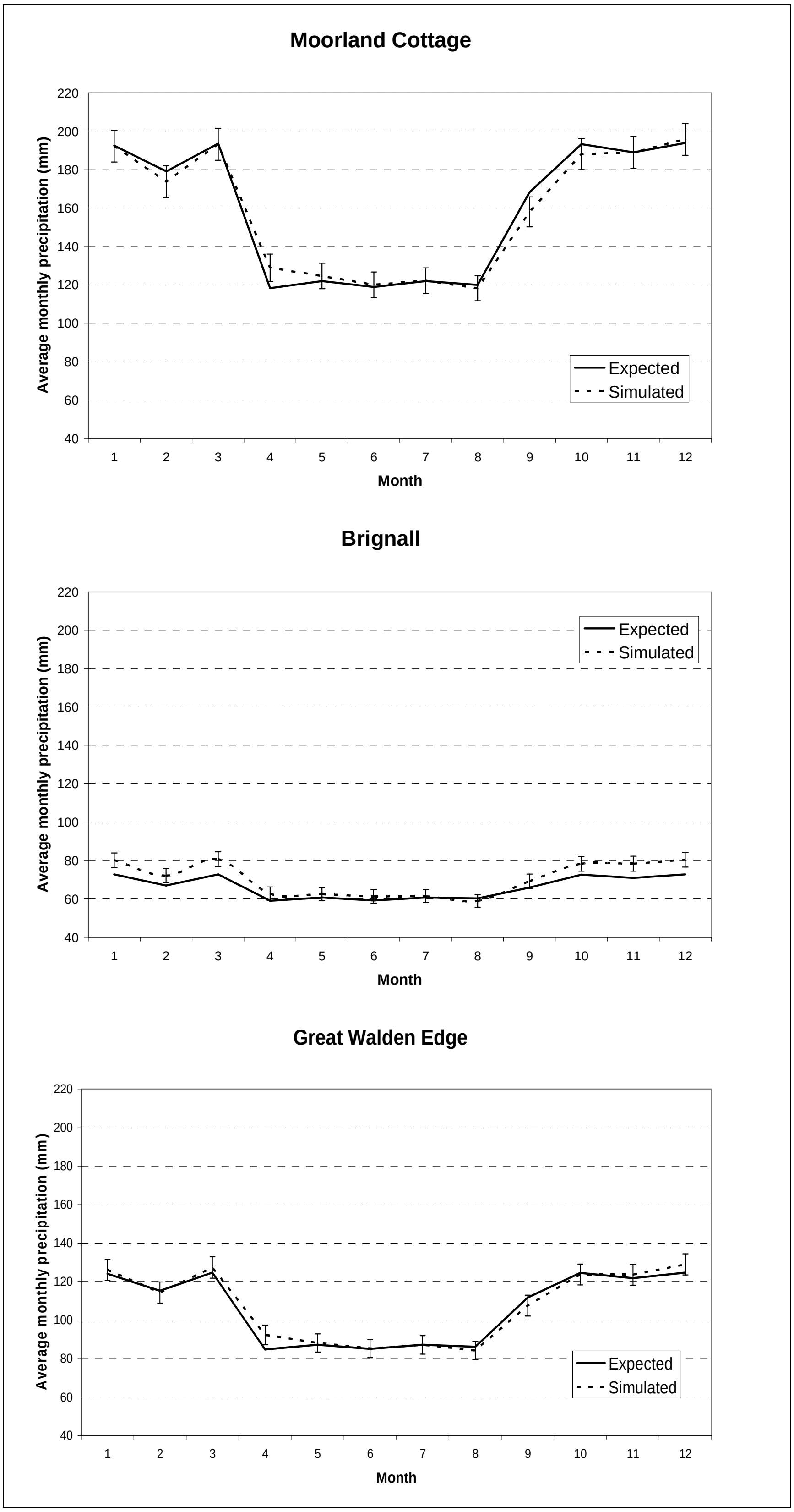

Figure 5. Comparison of expected and simulated monthly mean precipitation (mm) at Moorland Cottage, Brignall and Great Walden Edge (western spatial NSRP model). One standard deviation either side of the mean is illustrated to show significance of differences.

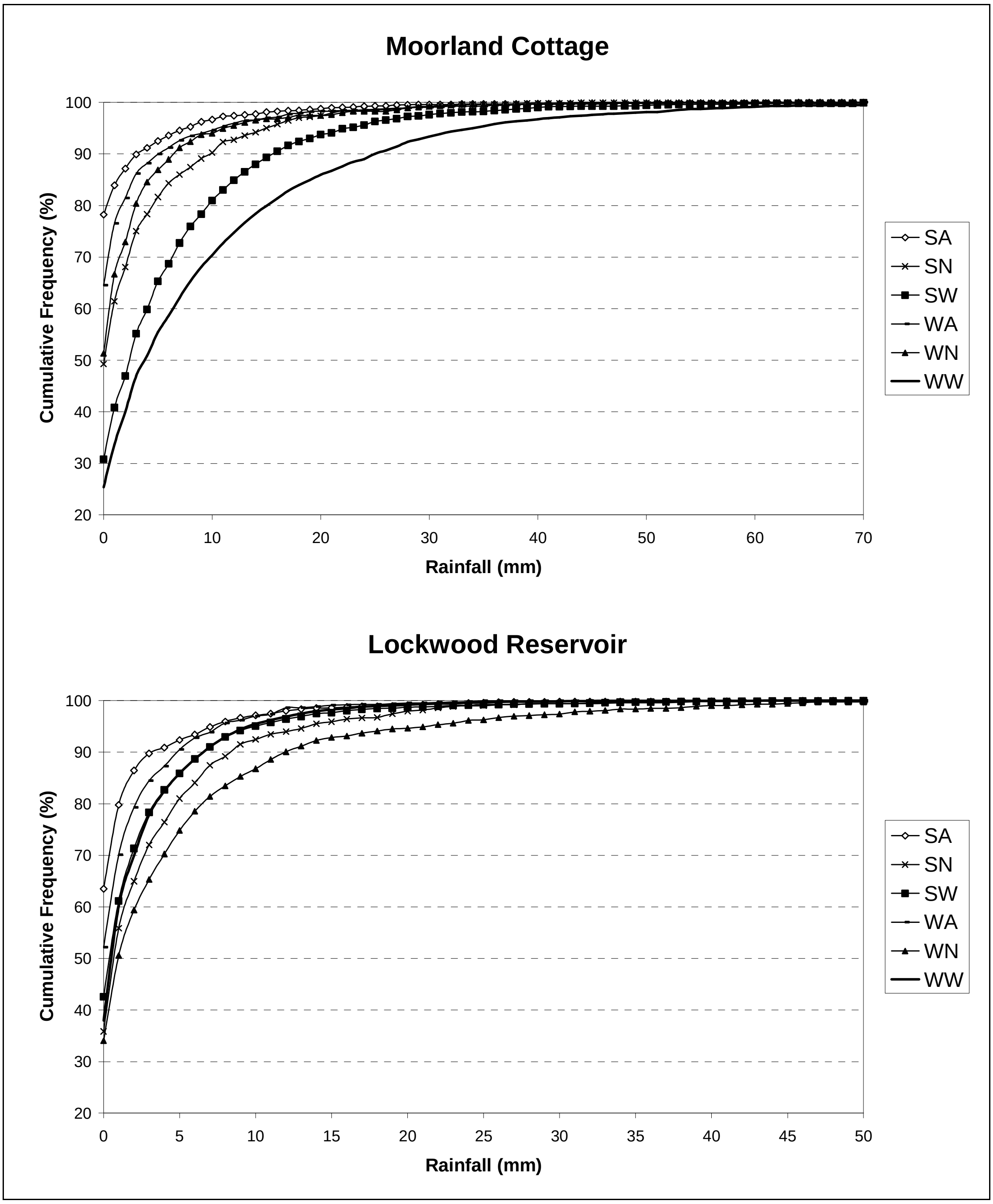

Figure 6. Rainfall amount frequency relationships for each of the six weather states at Moorland Cottage and Lockwood Reservoir. The maximum rainfall amounts far exceed the range of the graphs, e.g. WW at Moorland Cottage (maximum over 200 mm) and WN at Lockwood Reservoir (maximum over 100 mm).

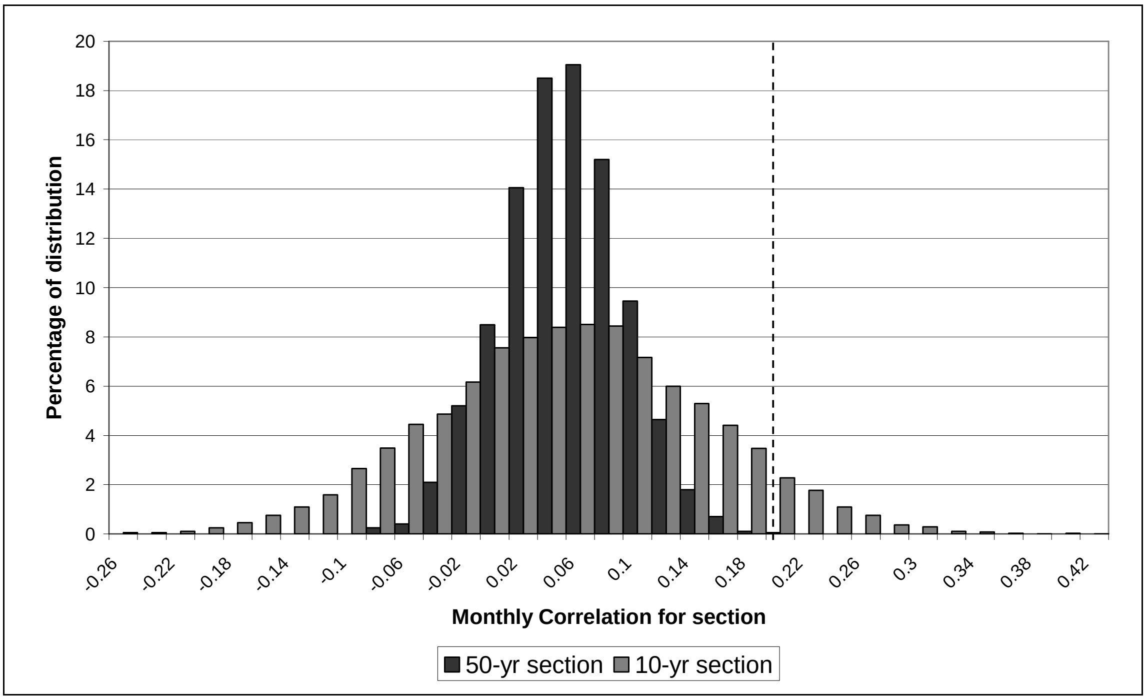

Figure 7. Comparison of distribution of simulated monthly spatial cross-correlations between Moorland Cottage and Lockwood Reservoir for 10-yr and 50-yr sections. Dashed line shows observed monthly spatial cross-correlation between the two sites using a 30-year data-set from 1961-1990.

Weather state	Objective Lamb weather types
Anticyclonic (A)	A, AE, ASE, AS, ASW
Northerly (N)	AN, ANE, N, NE, CN, CNE, E, SE, CE, CSE
Westerly (W)	AW, ANW, S, SW, W, NW, C, CS, CSW, CW, CNW

Table 1. Weather type groupings for the three weather states in both 'summer' and 'winter'.

Parameter	Explanation
λ (lambda)	storm origin arrival rate (h^{-1})
β (beta)	1/(mean waiting time for cell origins after the storm origin) (h^{-1})
ρ (rho)	mean cell density associated with a storm origin (km^{-2})
η (eta)	1/(mean duration of a cell) (h^{-1})
ξ (xi)	1/(mean cell intensity) ($h\ mm^{-1}$)
γ (gamma)	1/(mean cell radius) (km^{-1})

Table 2. The parameters of a single-cell type spatial NSRP model.

Annual	Moorland Cottage	Lockwood Reservoir	Kirk Bramwith
Moorland Cottage	−	0.24 (0.21)	0.21 (0.20)
Lockwood Reservoir	0.24 (0.21)	−	0.69 (0.68)
Kirk Bramwith	0.21 (0.20)	0.69 (0.68)	−

Table 3. Historical spatial cross-correlation of annual and monthly (bracketed) rainfall totals from 1961-1990 between the 3 index sites prior to the amalgamation of the two easterly sub-regions.

(a)

Parameter Weather State	μ(24) obs	μ(24) fitted	μ(24) sim	ϕ(24) obs	ϕ(24) fitted	ϕ(24) sim	V(24) obs	V(24) fitted	V(24) sim	V(48) obs	V(48) fitted	V(48) sim
SA	1.29	1.29	1.30	0.77	0.73	0.81	20.20	13.48	15.91	43.79	43.30	35.23
SN	2.76	2.76	2.77	0.44	0.38	0.41	33.70	21.17	20.04	77.41	60.08	56.65
SW	5.74	5.73	5.92	0.31	0.31	0.26	80.60	76.70	65.47	169.96	177.14	165.46
WA	2.43	2.44	2.54	0.57	0.58	0.56	39.20	29.54	24.70	91.15	88.81	56.97
WN	2.64	2.65	2.68	0.36	0.32	0.33	30.40	18.17	15.81	64.68	52.99	40.52
WW	8.79	8.80	8.97	0.23	0.21	0.16	152.70	124.10	106.05	362.06	355.51	314.82

(b)

Parameter Weather State	μ(24) obs	μ(24) fitted	μ(24) sim	ϕ(24) obs	ϕ(24) fitted	ϕ(24) sim	V(24) obs	V(24) fitted	V(24) sim	V(48) obs	V(48) fitted	V(28) sim
SA	0.62	0.64	0.64	0.81	0.80	0.82	5.70	4.34	4.37	13.19	14.08	14.10
SN	2.39	2.40	2.41	0.42	0.39	0.44	25.60	19.93	20.01	63.46	49.07	49.19
SW	2.61	2.62	2.64	0.44	0.41	0.46	29.10	22.74	22.85	62.36	57.88	57.77
WA	0.92	0.93	0.93	0.63	0.60	0.66	4.90	4.10	4.10	10.76	11.85	11.92
WN	2.73	2.76	2.73	0.41	0.39	0.44	22.80	21.34	21.23	93.16	67.20	66.94
WW	2.36	2.38	2.37	0.38	0.36	0.41	18.10	15.31	15.24	39.85	42.44	42.34

Table 4. Observed, fitted and simulated statistics for (a) Moorland Cottage, the index site for the western model and, (b) Osmotherly Filters, the index site for the eastern model: μ(24) (mean 24-hr rainfall), ϕ(24) (proportion dry days), V(24) (variance of 24-hr rainfall amounts), V(48) (variance of 48-hr rainfall amounts).

Parameter		λ (h^{-1})	β (h^{-1})	ρ (km^{-2})	η (h^{-1})	ξ (h mm^{-1})	γ (km^{-1})
Weather State	Model						
SA	Western	0.0010	0.0101	0.0388	0.1485	4.9862	0.0760
	Eastern	0.0006	0.0100	0.1462	11.9418	0.1814	0.0975
SN	Western	0.0035	0.0100	0.0260	7.9029	0.1369	0.0672
	Eastern	0.0110	0.0276	0.0020	1.0843	0.6754	0.0424
SW	Western	0.0234	0.0630	0.0020	11.9636	0.0395	0.0511
	Eastern	0.0125	0.0420	0.0020	0.2889	2.3424	0.0455
WA	Western	0.0018	0.0101	0.0246	0.6386	1.1660	0.0590
	Eastern	0.0031	0.0216	0.0134	7.2232	0.3266	0.0536
WN	Western	0.0039	0.0100	0.0200	0.9204	1.3531	0.0578
	Eastern	0.0028	0.0101	0.0291	0.2461	4.7707	0.0609
WW	Western	0.0206	0.0534	0.0041	0.1000	3.5412	0.0627
	Eastern	0.0044	0.0100	0.0020	0.3021	2.9205	0.0250

Table 5. Fitted parameters for the eastern and western spatial NSRP models.

Model	Mean correlation	Maximum correlation	Minimum correlation
Re-sampling	0.02	0.21	-0.14
NSRP + Sampling	0.09	0.28	-0.10

Table 6. Simulated mean, minimum and maximum monthly correlation statistics between each of 100 simulations of the 1961-1990 period at Moorland Cottage and Lockwood Reservoir using the NSRP model + sampling and re-sampling approaches.

Season	2021-2050	
	Rainfall amount change (%)	Rainfall variability change (%)
Summer	–5	+10
Winter	+9	+5
Annual	+3 to +5	–

Table 7. UKCIP98 climate change scenario for 2021-2050: rainfall amount and variability change.

		High-phase NAO % change from Baseline
East	Summer	+0.0
	Winter	+1.0
West	Summer	–1.0
	Winter	+2.0

Table 8. Changes in winter and summer rainfall receipt resulting from a high-phase NAO when compared to the baseline 1961-1990.

		2021-2050	
		$\mu(24)$	V(24)
Eastern	SW	2.40	32.0
	WW	2.68	19.0
Western	SW	5.37	88.7
	WW	9.52	160.3

Table 9. UKCIP98 climate change scenario for 2021-50: changes to mean daily rainfall and variability statistics.

Parameter		λ (h^{-1})	β (h^{-1})	ρ (km^{-2})	η (h^{-1})	ξ (h mm^{-1})	γ (km^{-1})
Weather State	Model						
SW	Western	0.005	0.010	0.007	0.131	2.682	0.052
	Eastern	0.002	0.011	0.028	2.171	0.418	0.067
WW	Western	0.031	0.245	0.002	0.100	3.146	0.062
	Eastern	0.017	0.079	0.003	6.227	0.240	0.041

Table 10. Fitted parameters for 2021-50 climate change scenario.