Hydrology and Earth System Sciences, 4(2), *263–282* (2000) © EGS

A stochastic rainfall model for the assessment of regional water resource systems under changed climatic conditions

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Abstract

A stochastic model is developed for the synthesis of daily precipitation using conditioning by weather types. Daily precipitation statistics at multiple sites within the region of Yorkshire, UK, are linked to objective Lamb weather types (LWTs) and used to split the region into three distinct precipitation sub-regions. Using a variance minimisation criterion, the 27 LWTs are clustered into three physically realistic groups or 'states'. A semi-Markov chain model is used to synthesise long sequences of weather states, maintaining the observed persistence and transition probabilities. The Neyman-Scott Rectangular Pulses (NSRP) model is then fitted for each weather state, using a defined summer and winter period. The combined model reproduces key aspects of the historic precipitation regime at temporal resolutions down to the hourly level.

Long synthetic precipitation series are useful in the sensitivity analysis of water resource systems under current and changed climatic conditions. This methodology enables investigation of the impact of variations in weather type persistence or frequency. In addition, rainfall model statistics can be altered to simulate instances of increased intensity or proportion of dry days for example, for *individual* weather groups. The input of such data into a water resource model, simulating potential atmospheric circulation changes, will provide a valuable tool for future planning of water resource systems. The ability of the model to operate at an hourly level also allows its use in a wider range of hydrological impact studies, e.g. variations in river flows, flood risk estimation etc.

Keywords: water resources; climate change; impacts; stochastic rainfall model; Lamb weather types

Introduction

Both observational and GCM (General Circulation Model) future scenario data suggest a recent amplification of climatic contrasts across the UK (Hulme and Jenkins, 1998). There have been significant shifts in the spatial and temporal distribution of precipitation (Mayes, 1995). This is seen most prominently in the marked increase in notable flood events and drought episodes and may profoundly affect water resource systems in vulnerable areas, as exemplified by the 1995 Yorkshire drought (Marsh and Turton, 1996). Linking the frequencies and characteristics of floods and droughts to the prevalence of dominant synoptic weather patterns may provide information on the performance of a water resource system under future, possibly slightly altered, climatic conditions.

The acknowledged lack of accurate information given by GCMs on the potential hydrological impacts of climate change (Rind *et al.*, 1992; McGuffie *et al.*, 1999) at sub-grid scales has directed research into utilizing the synoptic-scale output of GCMs in regionally-based models (e.g. Wilby, 1994). Both dynamical downscaling methods using RCMs (Regional Circulation Models) and statistical methods have been developed. The statistical methods implicitly assume a close relationship between atmospheric circulation patterns and local climatic variables such as precipitation, temperature, and potential evaporation. To date, many such linkages have been made for both large- and small-scale regions. Studies include Europe (Bardossy and Plate, 1992; Brandsma and Buishand, 1997; Goodess and Palutikof, 1998; Corte-Real *et al.*, 1998), the British Isles (Conway *et al.*, 1996; Conway and Jones, 1998; Wilby, 1997; Kilsby *et al.*, 1998), the United States (Hay *et al.*, 1991; Hughes and Guttorp, 1994) and Japan (Wilby *et al.*, 1998).

However, regional climate change prediction is regarded as a "*cascade of uncertainty*" (Mitchell and Hulme, 1999, p57) by many researchers. This is partly due to the uncertain future stability of derived current-climate relationships between circulation patterns and local weather elements (Wilby, 1997). For the British Isles, Wilby *et al.* (1995) have attributed this intra-weather class variability to subtle changes in the dominant precipitation mechanism (whether stratiform or convective), whereas Sweeney and O'Hare (1992) have suggested changes in the intensity of circulation development or changes in depression trajectories as contributing factors. To date, however, no rainfall model has incorporated the ability to modify internal weather class properties, to simulate changes which may be occurring, e.g. due to the UK precipitation intensity changes recently examined by Osborn *et al.* (2000).

This paper presents the development of a regional stochastic rainfall model based on a weather type approach with a spatial element. The spatial dimension of the model allows the concurrent simulation of precipitation series for very different climatological sub-regions within the same water resource area. This multiple site generation of precipitation has been previously demonstrated by Wilks (1998) using the Richardson (1981) weather generator, WGEN, but with no use of weather type information. In Yorkshire, this split is between the east and west of the region, as the dominant 'westerlies' bring much precipitation to the high ground of the Pennines in the west, with lower precipitation in the lee to the east. Conversely, in easterly airflows, most precipitation falls in the east, with little reaching the Pennines.

The normal precipitation pattern has resulted in the installation of supply reservoirs, predominantly in the Pennines to the west of the region. The model described here has been developed as part of a study investigating the effects of variations in the normal spatial pattern, which in the 1995–1996 drought resulted in severe stress to the Yorkshire water supply, necessitating the emergency measure of tankering water from outside of the region.

The coupling of a semi-Markov based weather generator, parameterized on historical data, with a stochastic rainfall model, such as the NSRP model (e.g. Cowpertwait *et al.*, 1996*a*,*b*), is also extremely powerful. It permits investigation into not only the impacts of variations in weather type persistence or frequency, as well as the alteration of rainfall model statistics to simulate instances of increased intensity or proportion of dry days for example, for an *individual* weather class. This technique may provide a valuable tool for future water resource management if climatic trends, both observed and modelled, can be translated into hydrological impacts.

Division of Yorkshire into coherent precipitation sub-regions

To allow the spatial modelling of precipitation within a water resource area that contains climatologically dissimilar sub-regions, the region must be split into coherent precipitation zones. In a similar analysis to that of Wigley *et al.* (1984) for England and Wales, precipitation sub-regions were determined for Yorkshire using 150 sites, each with at least 10 years precipitation data available during the period 1961–1990 (Fig. 1). Monthly totals at the 150 sites were cross-correlated with each of six sites that are evenly distributed across the Yorkshire region and provide a complete record for the 1961–1990 period: Moorland Cottage (MC), Kirk Bramwith (KB), York, The Retreat (YR), Hull, Pearson Park (HP), Lockwood Reservoir (LR) and Great Walden Edge (GW) (listed in Table 1; Fig. 1). Spline interpolation was used to produce a cross-correlation contour map for each of the six sites.

Wigley *et al.* (1984) suggested 0.7, approximating fifty percent of the variance, as a critical correlation level, in the case of their work allowing the delineation of eastern- and western-sides of the Pennine range of Northern England. Areas exceeding this critical correlation for each of the six sites were used to demarcate Yorkshire into three sub-regions. The west of Yorkshire was shown as distinct from the eastern sub-region, and bounded by the eastern edge of the Pennines. The area encompassing the North York Moors and Teesside was also shown as distinct from the southeastern sub-region. This suggests that the Yorkshire region should be split into three parts. These can be seen in Fig. 2 and are labelled 1, 2, and 3 for the 'Pennine', 'northeastern' and 'southeastern' regions respectively.

Weather type classification

An automated method of weather type classification, based on Lamb's weather types, and developed by Jenkinson and Collinson (1977) was used in model development. The scheme is based on the single, widely available, free atmosphere variable of daily-gridded mean-sea-level pressure (MSLP) and categorises surface flow by direction (in intervals of 45°) and synoptic type, and compares favourably with the subjective Lamb (1972) scheme on which it is based. Days are classified using three indices of airflow: total shear vorticity, strength of the resultant flow, and overall direction of flow (Jones *et al.*, 1993). The objective scheme contains a complete classification of daily atmospheric flow over the British Isles from 1880 and continues to be updated (http://www.cru.uea.ac.uk/cru/data/lwt.htm). The Lamb scheme, however, ceased in 1997. Another important advantage of the objective scheme is that it can be applied to other parts of the world.

The objective Lamb weather type (LWT) classification contains eight directional types; north (N), north-east (NE), east (E), south-east (SE), south (S), south-west (SW), west (W), and north-west (NW), and two non-directional types; anticyclonic (A), cyclonic (C). The directional and non-directional types can also be combined to define more complex circulation types as 'hybrid' types, for example the cyclonic westerly (CW). In addition, an unclassifiable (U) type is provided. This gives 27 possible weather types.

Weather type grouping

The grouping of weather types is necessary to reduce model complexity and the effects of over-parameterization of the

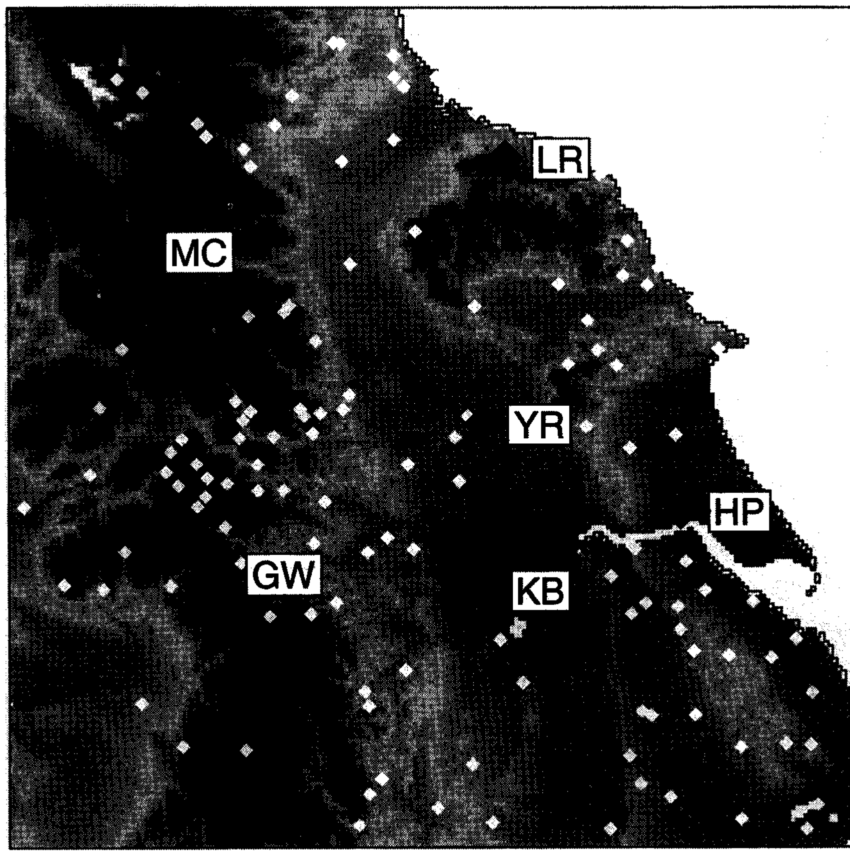

Fig. 1. *The locations of the 150 Yorkshire rainfall gauges used in regional division with an underlay elevation map (dark areas show highest elevation), reaching around 700 m.*

precipitation process within the less frequently occurring weather types. Within Yorkshire, the overriding spatial precipitation feature is the high precipitation amounts provided by westerly weather types to the western, Pennine sub-region. However, northerly and easterly weather types are the main precipitation-bearers for eastern sub-regions.

To enable spatial cross-correlation within a rainfall generator it is necessary to have the same weather type groupings for each sub-region. To formulate physically realistic groups, k-means clustering was applied separately to each of the three sub-regions using weather type specific seasonal statistics for mean daily precipitation and propor-

Table 1. Statistics for the six sites used in sub-regional delineation analysis. Rainfall statistics are for the period 1961–1990.

Site	Altitude (m)	Missing and suspect (%)	Mean annual rainfall (mm)	Mean annual proportion dry days	Max daily rainfall (mm)
Lockwood Reservoir (LR) (northeastern sub-region)	193	1.70	803	0.45	104.6 (Sep)
Hull, Pearson Park (HP) (southeastern sub-region)	2	0.29	658	0.51	70.4 (Sep)
Moorland Cottage (MC) (Pennine sub-region)	343	2.49	1939	0.41	102.6 (Apr)
The Retreat, York (YR) (southeastern sub-region)	18	0.56	640	0.54	67.9 (Jul)
Great Walden Edge No. 1 (GW) (Pennine sub-region)	346	1.52	1342	0.37	74.7 (Jul)
Kirk Bramwith (KB) (southeastern sub-region)	7	4.18	593	0.58	74.9 (Jul)

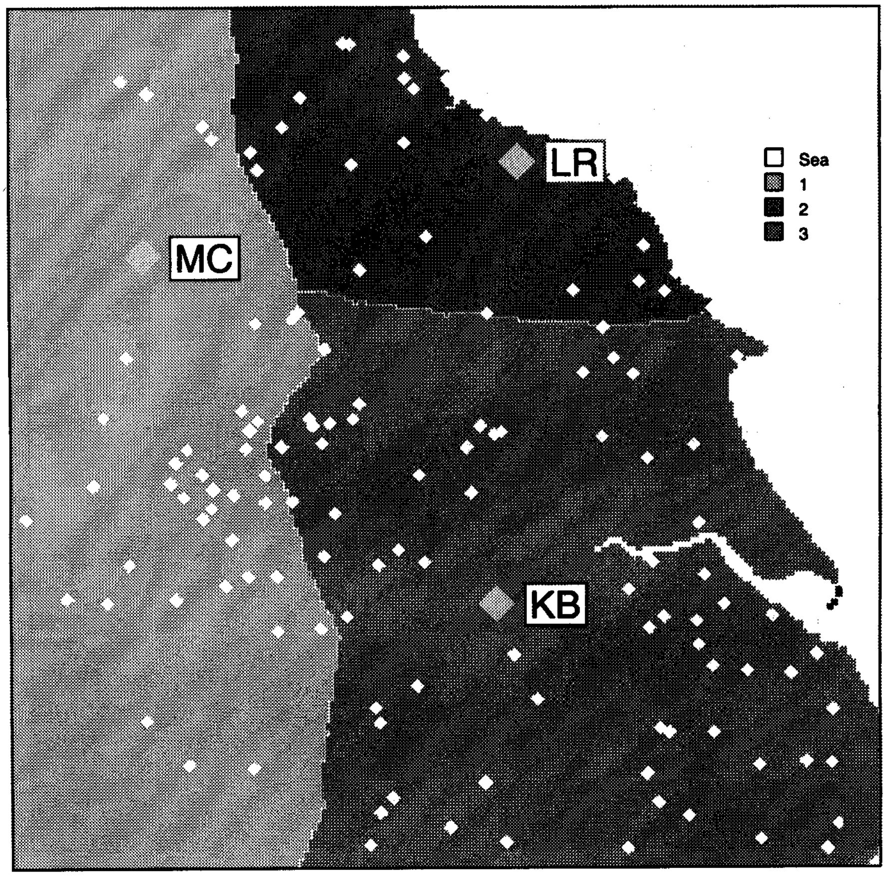

Fig. 2. *Yorkshire precipitation sub-regions generated by the cross-correlation analysis.*

tion dry days at each of the six sites. These provide good spatial and altitudinal coverage of Yorkshire. This gave two, one and three sites in the Pennine, northeastern and southeastern sub-regions respectively (details in Table 1).

The k-means algorithm is based on Hartigan and Wong (1979) and its objective is to find group memberships that minimise the total within-cluster sum of squares over all k of the clusters. The objective function, ϕ, can be represented by (Corte-Real *et al.*, 1998):

$$\phi = \sum_{k=1}^{K} \sum_{j=1}^{M} \sum_{i=1}^{N_k} (x_{ijk} - \bar{x}_{jk})^2 \tag{1}$$

where K is the total number of classes, M is the number of variables used, N_k is the number of samples in the k-th cluster.

A sample is assigned to a cluster by minimisation of the Euclidean distance between the vector of observed values (variables) and the mean of all the variables within a cluster. The k-means algorithm regroups data until the optimal cluster membership combination is achieved and the samples no longer change clusters.

Little overall difference was found in weather grouping between the seasons of winter and spring, or those of summer and autumn and three groups adequately describe the spatial precipitation pattern in Yorkshire. Therefore, the weather type groupings were optimised using a variance minimisation algorithm. The year was split into two arbitrary six-month periods and daily precipitation variance within the weather group or 'state' was minimised to ensure optimal coherency of the groupings. All tested grouping combinations have a substantive physical basis from information obtained from the k-means clustering analysis and the unclassified weather type was omitted from testing.

Analysis of various different grouping combinations suggested that variance is minimised and persistence maximised by the grouping arrangement detailed in Table 2. It is suggested that years are split into a 'summer' period from April to September and a 'winter' period from October to March. Three weather state groupings are defined for each season, giving winter-anticyclonic (WA), winter-northerly (WN), winter-westerly (WW), summer-anticyclonic (SA), summer-northerly (SN) and summer-westerly (SW) weather states.

It may be noted that in meteorological terms these may be roughly defined as blocking (anticyclonic), zonal (westerly) and meridional (notherly), and that the northerly weather state contains both northerly and easterly Lamb weather types.

Table 2. Weather type group definitions for the three weather states in both 'summer' and 'winter'.

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

Generation of weather type series

MODEL DEVELOPMENT

Many researchers have used Markov chain models to generate series of daily weather (e.g. Gregory *et al.*, 1992; Hughes and Guttorp, 1994), the simplest of which is the Richardson (1981) WGEN model. The approach taken here is similar to that of Hay *et al.* (1991). A discrete-time semi-Markov process is used to describe the occurrence of daily weather types. Transitions between states are modelled using the theory of Markov chains. However, additionally, the duration of a weather state is modelled by sampling from a distribution fitted to observed persistence properties. This is an extension to an alternating renewal process that generates sequences of wet then dry periods.

A finite set of three weather-type 'states' (W) has been defined. At an initial time, state i_0 is entered. An equal chance is given to the initial state being any one of the defined weather states for that season. After a random duration within this state, defined by a distribution fitted to the observed persistence probability distribution, the model enters state i_1. The process continues with a randomly defined duration within this state and then a transition to the next state, i_2.

The one-day transition probabilities are defined in two matrices A and B, where A denotes the 'summer' and B the 'winter' period. These matrices consist of transition probabilities A_{ij} and B_{ij} respectively, where i and j are in the set of **W**. The transition probabilities have values such that $0 \leq A_{ij}, B_{ij} \leq 1$ for all i and j and

$$\sum_{i=1}^{n} A_{ij} = 1 \quad \text{and} \quad \sum_{i=1}^{n} B_{ij} = 1, \tag{2}$$

where n is the number of states and $j = 1, n$. The alternating renewal process, by definition, defines within state transitions as zero, such that:

$$A_{ii}, B_{ii} = 0, \tag{3}$$

for i in the set of W (Mode, 1985). On a daily level, these are modelled using the persistence probability distribution for a weather state.

Transition probabilities were calculated using LWT data from 1881–1996. Hay *et al.* (1991) calculated the mean persistence time for each weather state and fitted a geometric probability distribution to these. However, in this case, transition probabilities for one-day transitions were temporally variable, depending upon the duration of the weather state (e.g. Fig. 3). For all weather states, within-state transition probability is significantly lower until the duration reaches at least three days. A significant difference was found between the observed and fitted geometric distribution using the chi-squared goodness-of-fit test. These differences were particularly prominent at the extremes, the geometric distribution underestimating the frequency of occurrence of both short and very long durations of some weather sequences, while overestimating the medium values. Extreme value distributions such as the

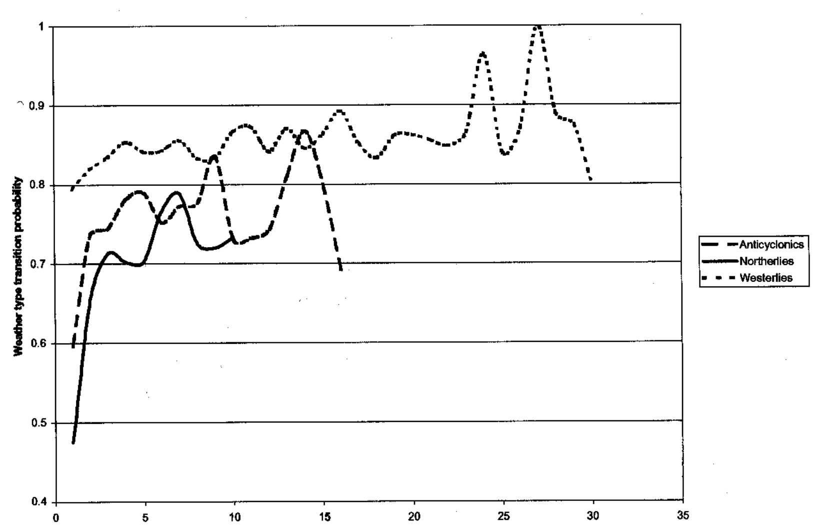

Fig. 3. *Weather state transition probabilities from a state to itself after different persistence durations for the 'winter' period.*

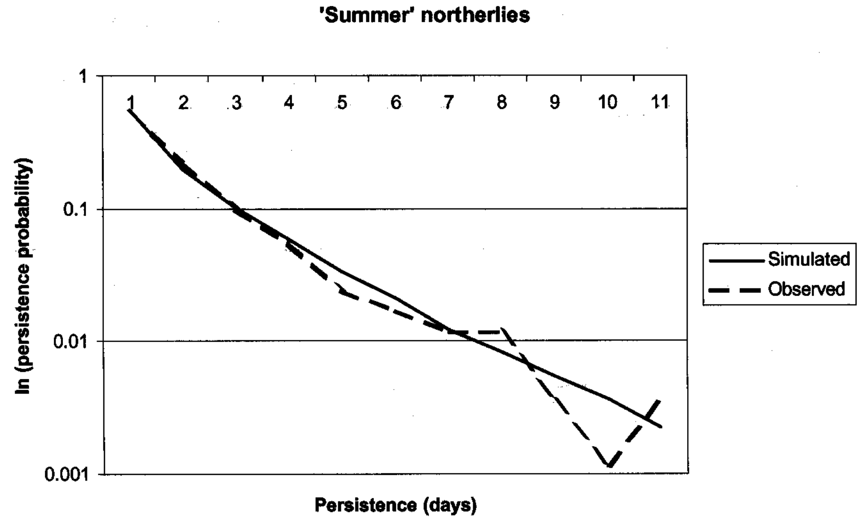

Fig. 4. *Comparison of the 99.5 percentile of observed persistence probability distribution against the fitted gamma distribution for the 'summer' northerlies.*

exponential or gamma distribution were therefore considered, and it was found that the gamma distribution provided the best fit to the persistence probability distribution for each weather state. Although this is a continuous distribution, it can be used as a discrete distribution as described below.

The gamma distribution is given by:

$$f(x, \alpha, \beta) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \quad (4)$$

When $\alpha = 1$, the exponential distribution results. Using integers for x-values cannot provide the required persistence probability distribution for the occurrence of one-day persistence. Therefore, x is replaced in the equation by $n - k$, where n is the number of days that a weather type state persists, and k is a positive non-integer ($k < 1$).

A gamma distribution was fitted to the persistence probability distribution of each of the six weather states using L-moments to fit the gamma distribution parameters (see Hosking, 1997) with values of k conditioned by the starting value of the distribution. The parameter values in Table 3 were obtained.

Table 3. Fitted gamma probability distribution parameters for the six weather states.

Parameter	'Summer'			'Winter'		
	A	N	W	A	N	W
k	0.349	0.330	0.400	0.280	0.300	0.411
alpha	0.591	0.549	0.727	0.461	0.480	0.691
beta	3.379	2.500	5.256	3.771	2.430	6.124

WEATHER-STATE MODEL VALIDATION

A Monte-Carlo experiment consisting of fifty 116-year simulated weather state was used to evaluate the capability of the model to generate synthetic series with statistics similar to those of the observed LWT 116-year series (1881–1996). Comparisons were made of modelled and observed transition and persistence probability distributions. The overall number of days of each weather state in the 116-year record and the simulated mean-, minimum-, maximum-occurrence, and variance were determined. Finally, a comparison was made of the observed and simulated distribution of annual daily occurrence of a weather state, ordered over the 116-year period.

Transition probabilities are fitted well by the semi-Markov chain model (Table 4). All errors are within two standard deviations from the observed value. The mean squared error (MSE) between the observed persistence probability distributions and the simulated persistence probability distributions is low and similar to the MSE between the observed and fitted distributions. The model is therefore capable of reproducing both observed transition and persistence probability distributions.

As a more rigorous check of model performance, the mean, maximum and minimum total number of days of each of the six weather states simulated by the model in the fifty 116-year simulated series, and the variance within the fifty series were compared against observed statistics. For these purposes the first and last year of each generated series were omitted, as the 'winter' season overlaps calendar years, leaving 114 years of data for comparison. The observed totals (Table 5), in all cases, lie within one standard deviation of the mean of the fifty simulated series, and annual errors are small. The mean annual model error in prediction is less than a day for all six weather states, the

Table 4. Observed and modelled transition-probability statistics, including within state probabilities, for the fifty Monte-Carlo 116-year series. Error refers to the observed transition probability minus the mean of the 50 simulated transition probabilities.

Statistic	'Summer'			'Winter'		
	A	N	W	A	N	W
Observed A	0.63	0.10	0.27	0.60	0.07	0.33
Modelled A						
Average	0.63	0.10	0.27	0.60	0.07	0.33
Maximum	0.65	0.11	0.29	0.62	0.08	0.34
Minimum	0.61	0.09	0.25	0.58	0.07	0.31
σ	0.01	0.01	0.01	0.01	0.00	0.01
Error	0.00	0.00	0.00	0.00	0.00	0.00
Observed N	0.22	0.52	0.26	0.26	0.47	0.27
Modelled N						
Average	0.22	0.53	0.26	0.25	0.48	0.27
Maximum	0.23	0.55	0.28	0.27	0.51	0.29
Minimum	0.21	0.50	0.23	0.24	0.46	0.24
σ	0.01	0.01	0.01	0.01	0.01	0.01
Error	0.01	−0.01	0.01	0.01	−0.01	0.01
Observed W	0.13	0.10	0.77	0.12	0.09	0.79
Modelled W						
Average	0.13	0.10	0.78	0.12	0.09	0.80
Maximum	0.14	0.10	0.78	0.13	0.09	0.81
Minimum	0.12	0.09	0.77	0.11	0.08	0.78
σ	0.00	0.00	0.00	0.00	0.00	0.01
Error	0.00	0.00	0.00	0.00	0.00	0.00

worst being the 'winter' northerly type with an over-prediction of 0.7 days yr^{-1}.

An analysis was also made of the annual statistics of maximum, minimum, mean daily occurrence and variance for each weather state (Table 6) using the fifty simulations. The mean annual occurrence of each weather state is well simulated by the model, with discrepancies of less than a day between observed and simulated statistics. Additionally, the

Table 5. Observed and simulated total number of days in 114 years of each weather state. Difference refers to the difference between average simulated and observed values (i.e. average – observed). Anomaly yr^{-1} refers to the number of days per year of each weather state that are over- or under-estimated by the model (i.e. difference/114).

Statistics	'Summer'			'Winter'		
	A	N	W	A	N	W
Observed	6032	3505	11325	5442	2813	12494
Simulated						
average	6015	3545	11302	5428	2892	12428
maximum	6362	3718	11686	5662	3086	12797
minimum	5759	3281	10896	5200	2710	12142
difference	−17	40	−23	−14	80	−66
σ	126.80	93.51	163.10	104.26	94.97	137.97
2σ	253.60	187.02	326.18	208.51	189.94	275.94
anomaly yr^{-1}	−0.15	0.35	−0.20	−0.12	0.70	−0.58

Table 6. Comparison of annual statistics for the observed and mean of the simulated fifty 114-year series. Ensemble maximum and minimum indicate the maximum or minimum total days in a year of that weather state within the fifty simulated 114-year series.

Statistic	Ensemble maximum	Maximum	Mean	Minimum	Ensemble minimum	Variance
'Summer'						
Observed A		85	52.9	27		153.8
Simulated A	93	83.3	52.8	25.9	15	133.2
Observed N		53	30.7	14		66.7
Simulated N	67	56.6	31.1	11.2	7	81.1
Observed W		129	99.3	69		166.6
Simulated W	145	132.4	99.1	65.0	49	177.0
'Winter'						
Observed A		78	47.7	25		133.5
Simulated A	93	78.8	47.6	21.7	11	125.3
Observed N		49	24.7	8		92.8
Simulated N	61	50.1	25.4	8.6	4	63.5
Observed W		136	109.6	75		181.3
Simulated W	157	140.8	109.0	73.1	58	170.6

means of the maximum and minimum simulated annual occurrence over the fifty simulations fit the observed maximum and minimum annual occurrence well. The ensemble minimum and ensemble maximum annual totals generated in the fifty simulated 114-year series are lower and higher, respectively, than the observed maxima and minima. Variance is generally under-estimated by the model.

The effect of errors in simulated variance and ensemble maxima and minima upon model performance was further investigated. The annual occurrence of each weather state was calculated for each year of the fifty 114-year simulations. These 114 annual totals were then ranked in ascending order for each of the fifty simulations, giving fifty ordered sequences for each weather state. For each rank, the mean of the fifty ordered sequences was calculated. This gave an expected distribution of annual totals for each weather type over a 114-year period. A similar procedure provided maximum and minimum error or uncertainty bounds about this distribution. The observed 114-year series was treated similarly and annual totals were ordered for each weather state.

Figure 5 shows the distribution of the 'summer' anticyclonic weather state. The error bands are small for all

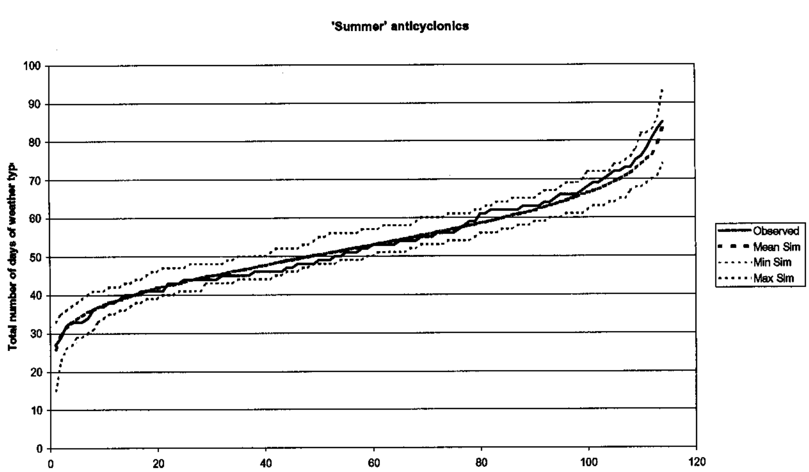

Fig. 5. *Total number of days occurrence of 'summer' anticyclonics for 114 years shown in an ordered sequence with boundary limits.*

weather states. The MSE between observed and mean simulated ordered sequences is low for all weather types, excepting that of 'winter' northerlies (WN). The model slightly overestimates the frequency of low annual occurrences of WN, and similarly underestimates the frequency of high occurrence, with a maximum of four days error for any one ranking. However, errors are in the order of one to two days annually, and model simulations are considered satisfactory.

Development of a rainfall model (WeatherSim)

EXPECTED REGIONAL PARAMETERS

The Neyman-Scott Rectangular Pulses (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 model has five parameters when fitted to a single site (Table 7). An analysis was made of the fitted model parameters that could be expected within the Yorkshire region. Parameters were fitted to daily precipitation data from 1961–1990 for each of the six sites detailed in Table 1 using a single-site model. The model fits were achieved on a monthly basis using the following sample moments: $\mu(1)$, $\phi(24)$, $\gamma(1)$, $\gamma(6)$, $\gamma(12)$, $\gamma(24)$ and $\gamma(48)$, $\rho(1)$, $\rho(6)$, $\rho(12)$, $\rho(24)$, $\rho(48)$, where μ is mean precipitation, ϕ is proportion dry, γ is variance, ρ is autocovariance and the number in brackets corresponds to the time period in hours (same terminology as Cowpertwait *et al.*, 1996*b*). Hourly variance statistics were derived from the daily variance using regression equations for the UK produced by Cowpertwait *et al.* (1996*b*).

The fitted λ^{-1} values provided a range for rate of storm arrivals of between two and six days. The highest rate occurs in autumn at Moorland Cottage (Pennines) with a storm origin every 1.8 days. The lowest rate occurs in May at Lockwood Reservoir (northeast region), with a storm origin every six days. Maxima are found for both the southeastern and northeastern sub-regions in autumn, with a minimum in the Pennines during this time. This may be due to an increase in northerly weather types during the months of September and October.

The mean waiting time for rain cell origins after the storm origin, β^{-1}, was between 24- and 48-hours in general. However, the minimum is under 10 hours at Hull (southeastern region) during November. Shorter mean waiting times are found in the winter than the summer, except at Pennine sites where mean waiting times are short throughout the year. The mean number of raincells per storm, v, shows an approximately sinusoidal relationship with maxima in winter and minima in summer at all sites. The mean number of raincells per storm is four to seven in winter and two to five in summer months, although more raincells are generated per storm at Pennine sites than elsewhere.

The fitted mean cell duration, η^{-1}, is always less than 12 hours. The southeastern sites and the Pennine site of Great Walden Edge have very low mean raincell duration, especially in winter months. Higher altitude sites, e.g. Lockwood Reservoir and Moorland Cottage, have a high fitted mean cell duration throughout the year. The mean cell intensity, $X\iota^{-1}$, has a maximum of 7 mm hr^{-1} at the high Pennine site of Moorland Cottage in winter months. In general, Pennine sites show a maximum in winter months and minimum in summer months. At eastern sites, and especially prominent at Lockwood Reservoir, the maximum intensity occurs during the months of September and October. This may be related to the marginal difference between the land and the North Sea surface temperature during these months, coupled with the increase in northerly weather types, bringing increased convective precipitation to the east of the region, which would be felt most at higher altitude sites.

FITTING OF WEATHER 'STATE' PARAMETERS (MODEL CALIBRATION)

Site seasonality was investigated prior to the NSRP fitting by analysing monthly mean daily precipitation for anticyclonic, westerly and northerly weather states at each of the three sites. These are plotted in Fig. 6. At Moorland Cottage, the mean daily precipitation distribution for the westerly weather state closely matches the distribution of observed mean daily precipitation. The mean daily precipitation totals for the westerly weather state in August

Table 7. The parameters of a one-cell NSRP model.

Parameter	Explanation
λ^{-1} (lambda)	the mean waiting time between adjacent storm origins (h^{-1})
β^{-1} (beta)	the mean waiting time for cell origins after the storm origin (h^{-1})
v (nu)	the mean number of type 1 rain cells associated with a storm origin (–)
η (eta)	the mean duration of a type 1 cell (h)
ξ (xi)	the mean cell intensity for type 1 cells (mm h^{-1})

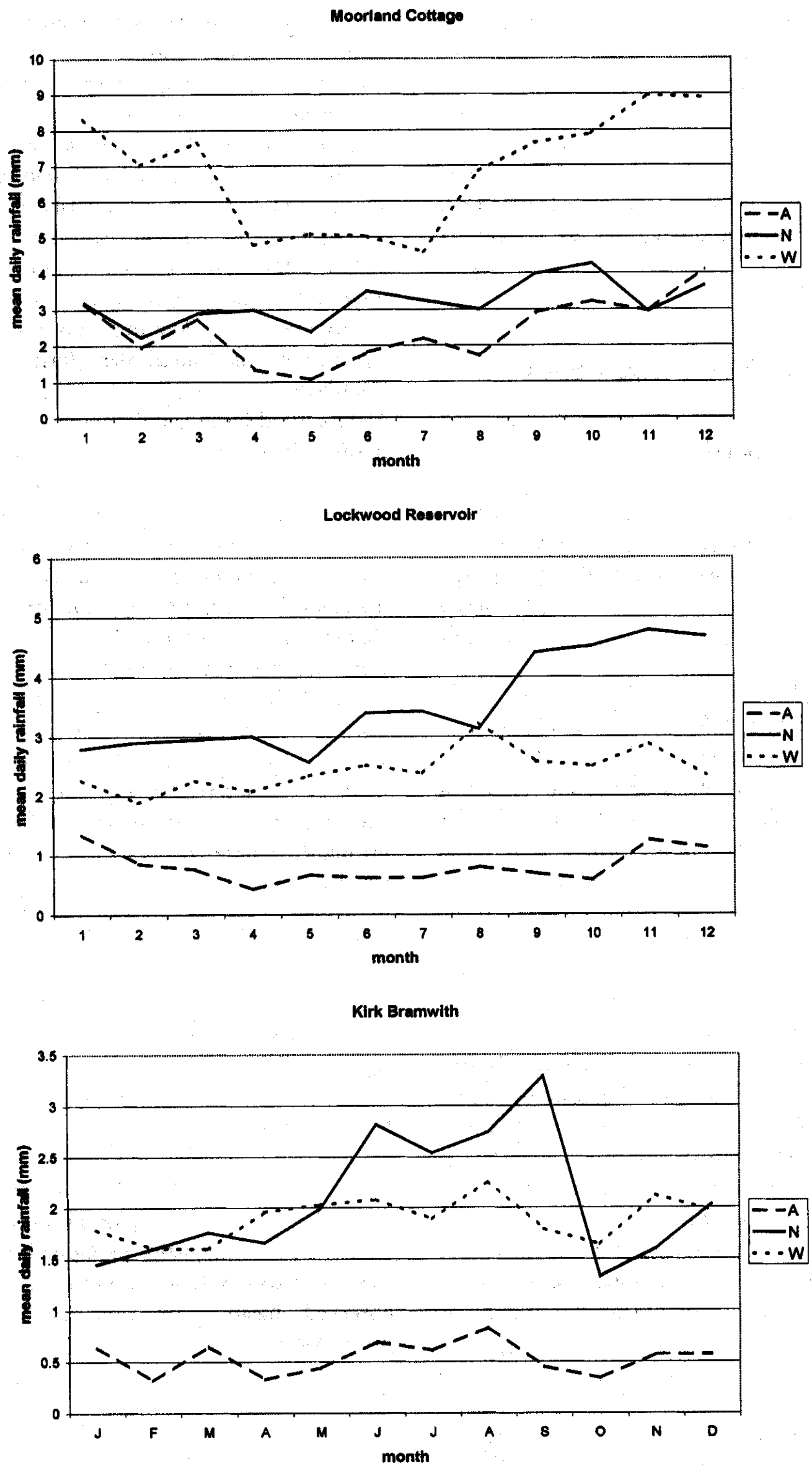

Fig. 6. *Monthly mean daily rainfall plotted for each weather state; anticyclonic, westerly and northerly, at Moorland Cottage, Lockwood Reservoir and Kirk Bramwith.*

and September are much higher than those of April, May, June and July, and in fact more akin to the winter totals. This reinforces the climatological fact that Pennine summers are very short. The year is split into two periods: April to August (season 1) and September to March (season 2). At Lockwood Reservoir, a relationship was found between the northerly weather state and observed mean daily precipitation totals. The northerly weather state

Table 8. The fitted parameters for a one-cell model.

Parameter Weather state	Site	λ^{-1} (h^{-1})	β^{-1} (h^{-1})	ν (−)	η (h)	ξ (mm h^{-1})
SA	MC	0.0094	0.115	1.765	0.621	0.5241
	LR	0.0140	0.063	1.000	0.570	0.8692
	KB	0.0055	0.020	1.524	1.548	0.2162
SN	MC	0.0322	0.403	1.485	0.375	1.0583
	LR	0.0480	0.031	1.058	0.218	1.8642
	KB	0.0099	0.023	4.510	1.061	0.4147
SW	MC	0.0383	0.086	2.346	12.000	0.0308
	LR	0.0338	0.029	1.326	0.327	1.2471
	KB	0.0333	0.347	1.278	0.353	1.3951
WA	MC	0.0076	0.024	3.582	0.385	0.9094
	LR	0.0075	0.043	6.544	12.000	0.1007
	KB	0.0068	0.180	4.637	12.000	0.1180
WN	MC	0.0389	0.184	1.000	0.526	0.7598
	LR	0.0471	0.055	1.285	0.376	0.9351
	KB	0.0100	0.059	11.874	12.000	0.1404
WW	MC	0.0288	0.025	2.770	0.501	0.4293
	LR	0.0206	0.038	3.115	0.765	0.843
	KB	0.0159	0.086	5.545	12.000	0.0943

provides the highest precipitation totals to the northeastern region (Fig. 6) and splits the climatological year into two approximate intervals, January to June (season 1) and July to December (season 2). At Kirk Bramwith, the year can be split into two intervals, April to September (season 1) and October to March (season 2), based upon the northerly weather state precipitation distribution. Season 1 and season 2 are arbitrarily titled 'summer' and 'winter' in each case.

The NSRP parameter fitting of the six weather states was achieved using a representative site for each sub-region: Moorland Cottage for the Pennines, Lockwood Reservoir for northeastern, and Kirk Bramwith for southeastern. Daily precipitation data for the 30-year period from 1961 to 1990 were split into the six weather states for each of the three sites using the groups in Table 2. 'Unclassified' days were omitted from the analysis. The model fit was achieved for each of the six weather states for each site using the fitting procedure detailed previously. Simulated series using these parameters provide a close match to observed statistics. The parameter values produced for the one-cell model can be found in Table 8, with a comparison of observed, fitted and simulated 24-hr statistics in Table 9.

The characteristics of the different weather states at the three sites can be derived from the fitted parameter values. For example, both the SA and WA states have low storm arrival rates coupled with a long mean waiting time for raincells after the storm origin. These characteristics are especially prominent in the Pennine and south-eastern

Table 9. Observed, fitted and simulated 24-hour statistics for each of the six weather states at each of the three sites.

Parameter Weather state	Site	$\mu(24)$	$\mu(24)$ fitted	$\mu(24)$ sim	$\gamma(24)$	$\gamma(24)$ fitted	$\gamma(24)$ sim	$\phi(24)$	$\phi(24)$ fitted	$\phi(24)$ sim
SA	MC	1.22	1.22	1.32	18.08	18.32	22.71	0.78	0.78	0.79
	LR	0.68	0.68	0.67	6.54	5.72	11.91	0.75	0.75	0.79
	KB	0.60	0.60	0.70	7.12	6.95	9.08	0.85	0.85	0.84
SN	MC	2.90	2.90	3.22	33.43	34.38	37.94	0.49	0.49	0.48
	LR	2.99	2.99	2.57	28.56	26.03	20.36	0.30	0.30	0.36
	KB	2.45	2.45	2.52	27.26	27.58	26.10	0.52	0.52	0.49
SW	MC	5.84	5.84	5.57	80.75	84.29	82.39	0.29	0.29	0.33
	LR	2.64	2.64	2.48	28.38	24.94	22.90	0.38	0.38	0.44
	KB	2.06	2.06	2.06	19.18	18.65	20.76	0.50	0.50	0.54
WA	MC	1.87	1.87	1.78	28.54	23.54	20.92	0.63	0.63	0.63
	LR	0.98	0.98	0.95	4.96	5.19	4.96	0.61	0.61	0.64
	KB	0.53	0.53	0.50	2.99	2.82	2.70	0.80	0.80	0.84
WN	MC	2.34	2.34	2.06	27.29	25.95	19.93	0.49	0.49	0.53
	LR	4.13	4.13	3.98	48.16	48.36	46.47	0.30	0.30	0.35
	KB	1.68	1.68	1.70	9.64	9.51	8.97	0.50	0.50	0.51
WW	MC	8.91	8.90	8.27	182.11	180.03	169.27	0.24	0.24	0.27
	LR	2.39	2.39	2.39	18.07	17.93	17.57	0.36	0.36	0.38
	KB	1.87	1.87	1.92	11.54	11.67	11.95	0.48	0.48	0.49

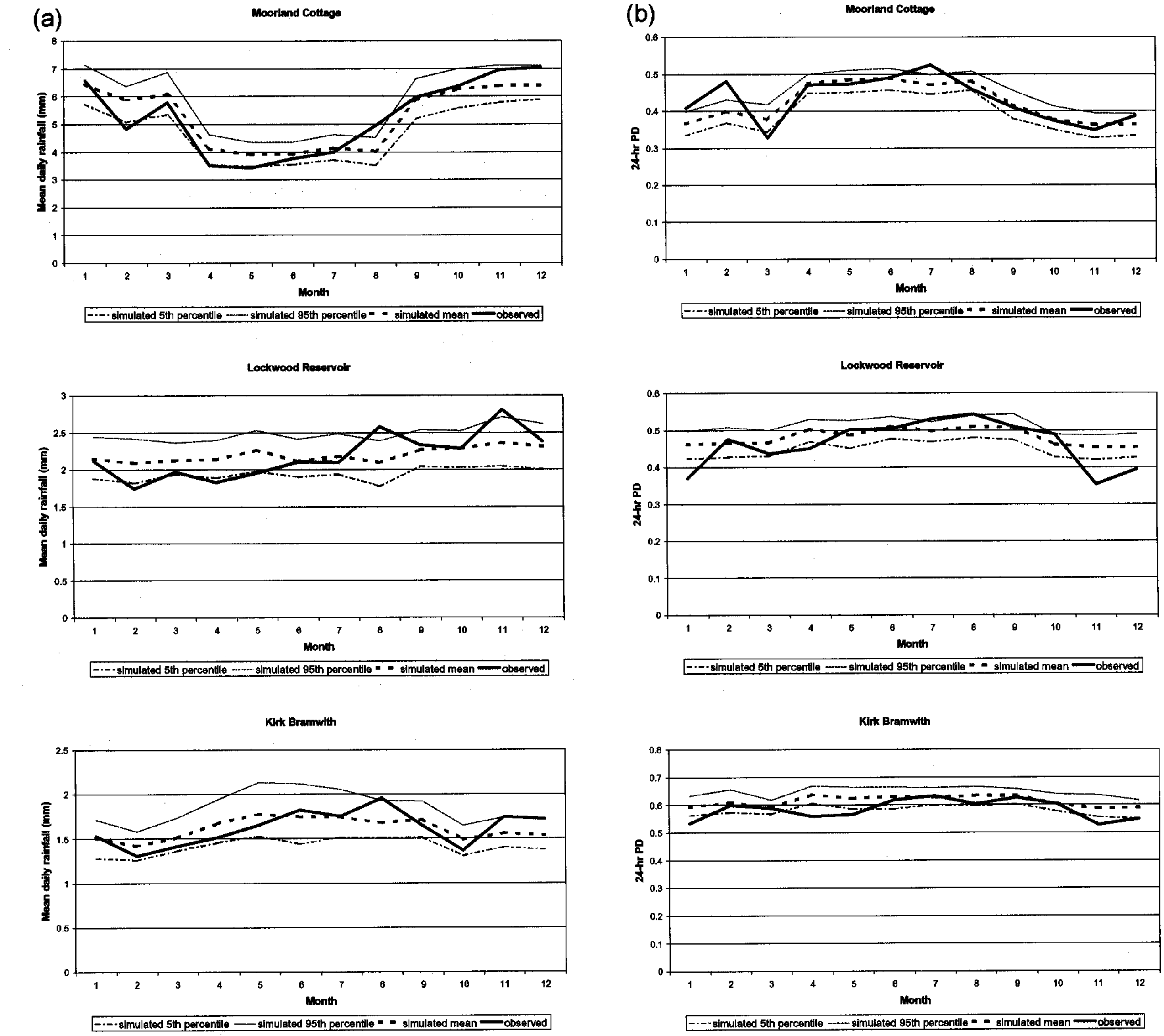

Fig. 7. *Observed, simulated mean, 5 and 95 percentile statistics for each calendar month using fitted parameters: (a) mean daily precipitation, (b) proportion dry days, (c) daily variance.*

regions, and produce a very dry weather type. The characteristics of SW and WW in the Pennines are also interesting. In the summer, the westerly weather state produces short-lived cells with high intensities, suggesting convective precipitation. However, in the winter the rain-cells are of longer duration with much lower intensities, consistent with frontal precipitation. These properties can be represented in a Generalised NSRP model by using two distinct cell types ('light' and 'heavy'), but at the expense of parsimony (Cowpertwait, 1995).

RAINFALL MODEL VALIDATION

Model validation was carried out in two stages. Firstly, an analysis was made of the effects of lag between weather state initiation and precipitation within the model upon the accuracy of simulated monthly statistics. Secondly, a Monte-Carlo experiment with fifty 30-yr simulations was undertaken using the historical LWT series to determine whether the correct monthly statistics were generated. Model error within the fifty synthetic series was also quantified.

The effects of lag

Model performance may be adversely affected by the lag between weather-state initiation, and generation of rain-cells associated with that weather-state. Fitted parameter values suggest that a lag from 1 to 10 days can be expected, for the wettest and driest weather state respectively. To demonstrate the lag-effects of a 'wet' weather state upon a 'dry' weather state, and vice versa, the year was split into four

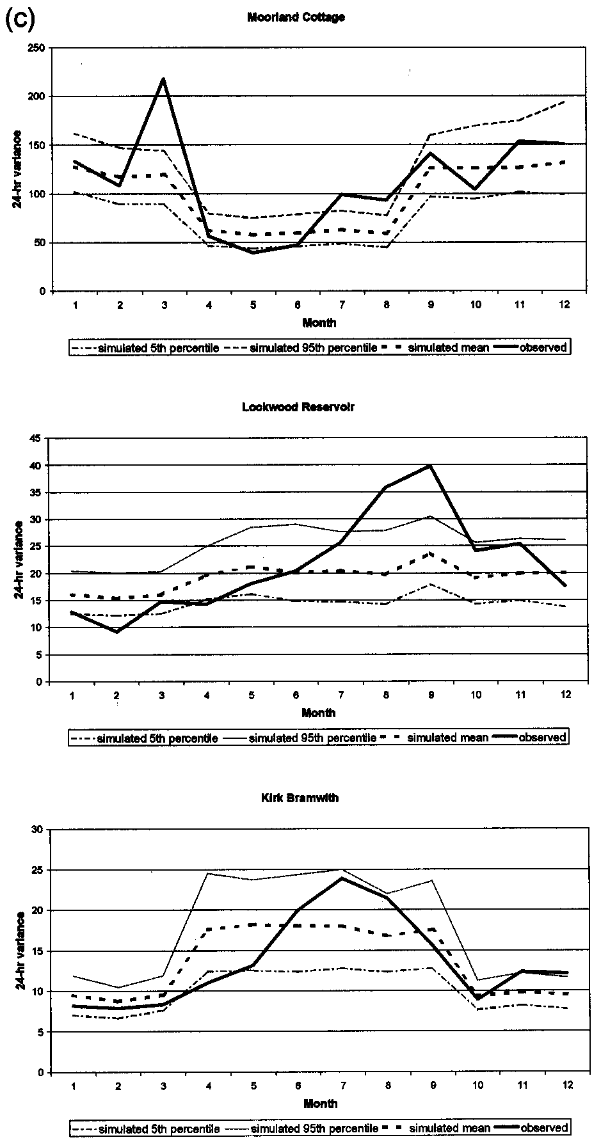

Fig. 7. *Continued.*

3-month periods: Jan–Mar, Apr–Jun, Jul–Sep, and Oct–Dec. The periods from January to March and from July to September were assigned a 'dry' weather state and the other two periods were assigned a 'wet' weather state, SA and SW from Moorland Cottage. This gave two crossover periods for a 'wet' to a 'dry' weather state (in January and July) and two for 'dry' to 'wet' (in April and October).

A lag-effect is discernible in the crossover months. This translates to an increase in mean precipitation in a 'dry' month preceded by a 'wet' month, and vice versa. However, the effect is short-lived, affecting only the first month of the 3-month period. There is an increase in the proportion of dry days (PD) in April and October, but no significant reduction for the crossover months of January and July. As the SA type is extremely dry and has a very high PD it is likely that the SW weather type provides the major effect on both types of crossover period. The lag causes a reduction in precipitation in a 'wet' month preceded by a 'dry' month. The lag-effect of the previous 'dry' month brings little additional precipitation to the 'wet' month. When coupled with the lag between the initiation of a 'wet' weather state and rain-cell generation this causes a decrease in mean daily precipitation at the beginning of the monthly period. However, other 'wet' months preceded by a wet month are supplied with rain-cells from initiated wet weather states of the previous month. Similarly, a 'dry' month that incurs rain-cells from a prior 'wet' month will have an increased mean precipitation statistic, but the PD statistic may not be severely affected.

Monte-Carlo analysis

A Monte-Carlo analysis consisting of fifty 30-year simulations was used to evaluate the model's ability in reproducing observed mean precipitation statistics from 1961–1990 at Moorland Cottage, Lockwood Reservoir and Kirk Bramwith. The historical LWT series translated into the appropriate weather states was used as input to the NSRP model. Monthly statistics for mean daily precipitation, PD and 24-hr variance were derived from the analysis and plotted against observed statistics. These included an average monthly statistic taken from all fifty 30-year simulations, and the 5 and 95 percentiles of the fifty simulations.

At Kirk Bramwith, all measured statistics are well simulated by the model (see Figs. 7(a)-(c)). The historical variability is captured, with a low day-to-day winter variance and large increases in summer months. The PD statistic is stable at approximately 0.6 for the entire year. At Lockwood Reservoir, the mean daily precipitation statistic is well simulated (Fig. 7(a)), observed statistics lying within the extremes of the simulated statistics. The PD statistic is well fitted (Fig. 7(b)), and an especially good match is obtained between May and August. The increased variability in precipitation during autumn months is also captured (Fig. 7(c)). 'Summer' variance is slightly under-predicted but the observed statistics, in the main, lie within the range of the simulated series.

At Moorland Cottage the mean daily precipitation and PD statistics are well matched (Figs. 7(a) and 7(b)), apart from the months of February and March which show highly unusual variation in the observed record. The observed variance is adequately reproduced (Fig. 7(c)), apart from the month of March itself which has very high variability. The model captures this variability to a certain extent but cannot be expected to produce such high values due to the averaging effect imposed by using additionally six other months in the model 'winter' fitting.

DISCUSSION

LIMITATIONS AND BENEFITS OF THE DOWNSCALING APPROACH

The main strength of this weather type stochastic rainfall model is the provision of a *transferable methodology* for classification, weather state simulation and subsequent precipitation modelling, thus overcoming a limitation previously identified by Wilby (1994). The LWTs provide a classification system that is easy to understand, simple to use and has a substantial physical basis in climatology. The LWT system has also been applied, with some success, to regions of both northern and southern Europe (e.g. Brandsma and Buishand, 1997; Goodess and Palutikof, 1998). Weather groups are delineated using the climatology of the water resource area being studied and weather types are grouped based on a simple variance minimisation routine. The over-parameterisation of the precipitation process within the less frequently occurring weather types noted by many researchers (e.g. Hay *et al.*, 1991; Wilby 1994) is also avoided by the production of weather state groups.

The flexibility of the approach is also important, with limited parameter re-calibration required for the immediate application to another area. The use of a semi-Markov chain model as a weather state generator requires the calibration of only three parameters for each weather state in an automatic routine. Transition probabilities can be taken directly from the observed record. The model provides accurate simulation of LWT groups and is applicable to other areas using NCEP reanalysis data. The NSRP model has been applied to many climate regions of Europe and worldwide, its flexible structure allowing a good fit to observed statistics.

Although the main aim of the current application is in water resource management where aggregated daily and monthly flows are required, the NSRP methodology provides reproduction of the precipitation statistics at the hourly level, facilitating more detailed impact studies e.g. variations in river flows, flood risk estimation etc.

The weather type approach is appealing as it is founded on physical linkages between climate at the large scale and weather at a local scale. However, there are many limitations. Wilby (1997) suggests some fundamental problems pertaining to issues of classification, scale and stability.

Firstly, downscaling approaches seldom capture spatial and temporal climatic variability at all scales, and there can be interdependence between variables. This is potentially the greatest problem for flood or drought analysis as it influences extremes. For example, Conway *et al.* (1996) compared two downscaling approaches and found that daily characteristics were generally well preserved but inter-annual variability was poorly reproduced.

Secondly, as atmospheric circulation is essentially dynamic then the identification of distinct 24-hr 'weather' types is arbitrary, even when very clearly defined criteria are applied. Even objective classification techniques contain a degree of subjectivity as the results are sensitive to internal parameters such as grid-size or number of different classes used (Yarnal *et al.*, 1988). Additionally, regional airflows may be apparent so that for example, it is often impossible to allocate a single weather type that is spatially representative of the whole UK (Mayes, 1991).

Finally, and perhaps the most serious hindrance to reliable future downscaling approaches (Wilby 1997), in many cases the relationship between weather type and its associated meteorological properties is constantly changing. Wilby (1994) found inter-decadal variability in both mean wet day precipitation amount and probability of precipitation associated with the three dominant Lamb weather type

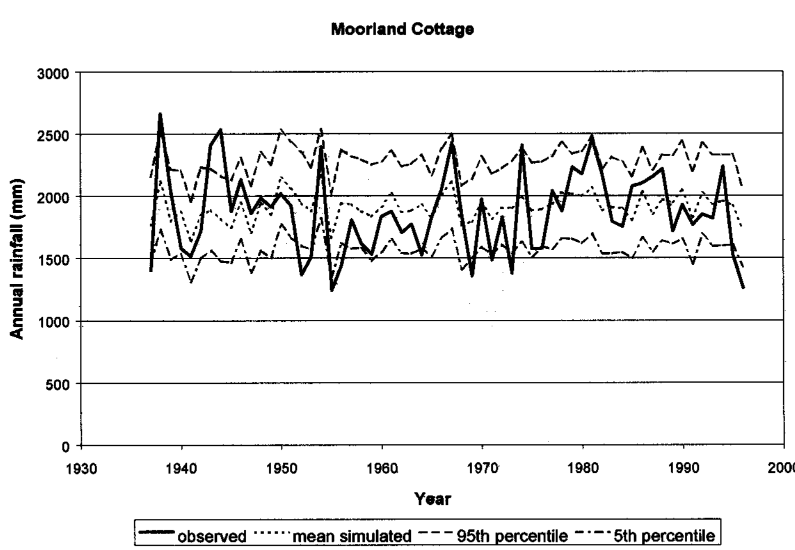

Fig. 8. *Observed and simulated annual rainfall totals at Moorland Cottage for 1937–1996, showing 5 and 95 percentiles.*

Table 10. Observed and simulated mean statistics for 50 simulations of the 1937–1996 period. Correlation refers to the correlation between the annual precipitation totals of the observed and mean simulated series. Standard deviation of the simulated series refers to the mean standard deviation of the simulations.

Site	Series	Correlation	Mean annual precipitation (mm)	Standard deviation
Moorland Cottage	Observed		1911	300
	Simulated	0.58	1930	225
Lockwood Reservoir	Observed		803	113
	Simulated	0.52	796	109
Kirk Bramwith	Observed		594	101
	Simulated	0.51	589	80

classes of A, C and W. Even assuming stability, the simulated precipitation regime may still be dependent upon the period chosen for model calibration.

A further characteristic or limitation of the method is imposed by the 'non-unique' nature of downscaling; a wide range of possible precipitation values may be equally likely associated with a single weather type or state. This means that the stochastic model series cannot be expected to reproduce one-to-one correspondence of precipitation amounts to observed weather types. Rather, the averaged statistical properties of the weather types should be reproduced.

Figure 8 gives an example of this behaviour. Fifty simulations were performed to provide mean, 5 and 95 percentile statistics of annual-precipitation totals for the 1937–1996 period, using the LWT record as input. The model does not reproduce exactly the historical annual precipitation totals due to its stochastic nature. However, it is able to simulate annual precipitation totals within historical limits. Table 10 gives the correlation between the observed annual precipitation totals and the mean annual total of the simulated series. The standard deviation of the observed and simulated series is also shown. All simulated series have reduced standard deviations. However, single simulations for all three sites produce levels of variability akin to observed levels. This behaviour is only a limitation if one-to-one correspondence with an observed series or a meteorological forecase is required. For most purposes the reproduction of mean statistics is sufficient.

INVESTIGATION OF THE BENEFIT OF CONDITIONING BY WEATHER STATE

Weather-state conditioning introduces a significant extra degree of complexity in the model. A purely stochastic approach is also possible, where an ensemble of possible

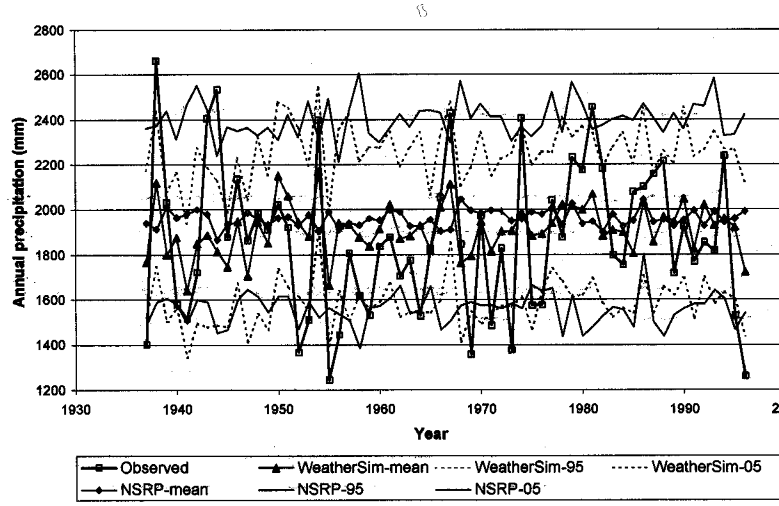

Fig. 9. *Comparison of simulated annual precipitation totals at Moorland Cottage for 1937–1996 using the NSRP model and WeatherSim (NSRP model using weather-type conditioning), showing 5 and 95 percentiles.*

Table 11. Simulated mean, minimum and maximum correlation statistics between observed annual totals and each of 50 simulations of the 1937–1996 period at Moorland Cottage using the NSRP model and WeatherSim. Standard deviation refers to the mean standard deviation of the 50 simulations.

Model	Mean correlation	Maximum correlation	Minimum correlation	Standard deviation
NSRP	0.01	0.26	−0.18	275
NSRP + weather type conditioning	0.24	0.48	0.08	225

precipitation series is generated, regardless of weather states. These series will contain sequences similar to observed precipitation and, by definition, contain statistically representative numbers of dry, wet and extreme months and years (e.g. Cowpertwait *et al.*, 1996*a*,*b*). Such a series is certainly useful for reliability testing of water resource systems, but will not necessarily allow a meaningful re-parameterisation for future climates or the production of correlated regional models for large spatial domains. However, for a conditioned model (i.e. with weather states) to be preferred it is first necessary to demonstrate the improved performance of such a model over the basic stochastic model.

An investigation was therefore made of the benefit of introducing weather type conditioning over the use of an NSRP model unconditioned by weather type information. The NSRP model was fitted to observed precipitation statistics at Moorland Cottage, on a calendar month basis, as described previously. Fifty simulations of 60-yrs duration at hourly resolution were produced and aggregated to annual totals. Mean, 5 and 95 percentile statistics were determined for each calendar year and are shown in Fig. 9, together with the equivalent statistics derived from the conditioned model. The conditioning of precipitation on synoptic weather types can be seen to reduce significantly uncertainty and increase explained variance. This is quantified by the increase in average correlation between observed annual totals and each of the fifty simulations using weather-type conditioning shown in Table 11. This is desirable, as it identifies the effect of weather state conditioning in both controlling the mean and reducing the spread of the precipitation amount distribution for each day and weather state.

The reduction in the conditioned 95th percentile is particularly apparent, and is due to the stipulation of a fixed (observed) proportion of dry weather states in the conditioned model. This will result in an upper limit on annual precipitation, as opposed to the case of the unconditioned model, which allows years to be simulated containing high totals generated with equal probability in all months or days regardless of weather state. The same limitation acts in reverse on the fifth percentile to a lesser degree, with a fixed proportion of wet weather states in the conditioned model.

The introduction of conditioning by weather type is justified by the improvement in explained variance as well as by two additional factors. The first of these is the ability to modify the model for future climate cases by changing proportions of weather states. The second is the capability to generate correlated series at two or more widely separated sites, conditioned by the same weather state. These capabilities are discussed in more detail in the next section.

SUITABILITY FOR CLIMATE CHANGE IMPACT APPLICATIONS

This weather type precipitation model was developed for use as a tool in climate change research, and particularly for the estimation of reliability for regional water resource systems. The weather type approach improves upon the 'factor' approach adopted by many researchers (e.g. Arnell and Reynard, 1996) and used by UK water companies in recent climate change assessments. That approach simply modified observed precipitation records by a factor change to the mean derived from GCM simulations, resulting in no changes to the temporal and spatial structure of the precipitation 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 precipitation. The methodology allows the results of GCMs to be used directly, via analysed GCM LWTs, or indirectly, as trends in both weather state and precipitation characteristics can be extracted and interpreted within the model. However, the use of model derived estimates of change must be very carefully justified as there are huge differences between models on a regional scale (McGuffie *et al.*, 1999.)

The coupling of weather states to local precipitation characteristics also contains a spatial element that has often been lacking in previous studies. The model allows the concurrent analysis of different water resource areas within a region that may have very different climatological patterns. Yorkshire is split into three zones that receive precipitation from diverse sources. This spatial variation is provided by the separate fitting of each weather state for a region.

Finally, the obstacle to downscaling arising from the

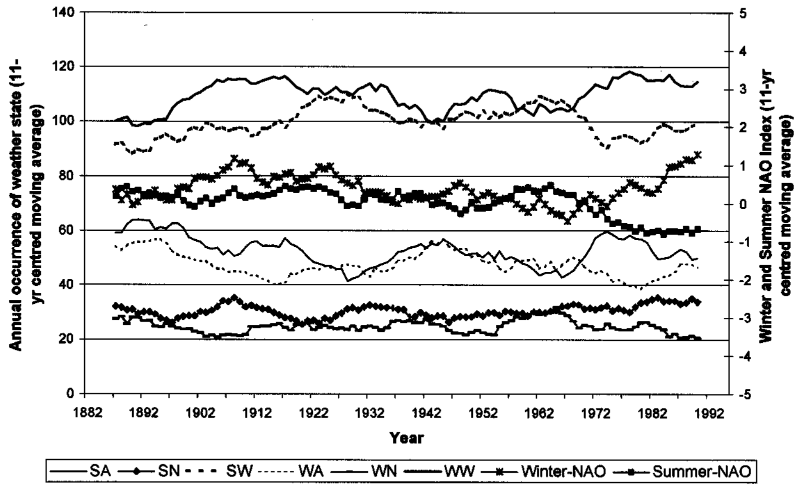

Fig. 10. *11-year centred moving averages of the winter and summer NAO and the six weather states.*

internal instability of a weather type itself (Wilby, 1997) may have been avoided to some extent. The methodology provides the opportunity to examine the effects of internal instability of a weather state upon precipitation statistics within a water resource region. Parameters within the NSRP model that have been fitted on precipitation information from 1961–1990, forming a baseline period, can be adjusted to quantify the effect upon spatial precipitation. In this way, recent concerns about change to precipitation intensities, mean characteristics or increased variability can be evaluated. This is in addition to the frequency and persistence characteristics of the weather states that can be investigated by adjusting probability distributions within the weather-state generator.

An example application of this approach involves the correlation of weather state frequencies with the North Atlantic Oscillation (NAO) (Jones *et al.*, 1997). The NAOI is a measure of pressure difference between Iceland and the Azores 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 (Osborn *et al.*, 2000) and a summer index is given by the May to July average. Figure 10 shows the 11-yr centred moving average of the summer- and winter-NAO and fitted weather states for the period 1882–1996. A clear correlation can be observed between the NAO indices and the frequency of weather states, especially the anticyclonic and westerly types. Significant correlations are shown in Table 12. Prominent inverse correlation is observed between the SW and SA, and WW and WA weather states respectively. During a high winter-NAOI 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. In a low-NAO period, such as 1961–1970, the reverse situation occurs.

To illustrate the use of NAOI, the semi-Markov chain model parameters were re-fitted on the period from 1980–1990 and the period from 1960–1970 to simulate high and low occurrences of the NAO. Fifty 30-year synthetic series of weather states were produced and precipitation simulated using the NSRP model. The high-NAOI simulation would be expected to show the enhanced seasonality that was observed in the 1980s and early 1990s. The low-NAOI simulation would conversely show reduced seasonality.

Table 12. Correlation coefficients between the summer and winter NAOI and the annual occurrence of the six weather states (bold signifies a significant correlation at the 95 percent level).

	SN	SW	WA	WN	WW	winter NAO	summer NAO
SA	−0.18	**−0.91**	**0.29**	−0.09	**−0.20**	0.00	−0.11
SN		**−0.24**	**−0.39**	−0.17	**0.40**	0.16	**−0.50**
SW			−0.12	0.16	0.03	−0.07	**0.31**
WA				0.17	**−0.90**	**−0.33**	**0.31**
WN					**−0.58**	**−0.73**	**0.46**
WW						**0.60**	**−0.46**
winter NAOI							**−0.25**

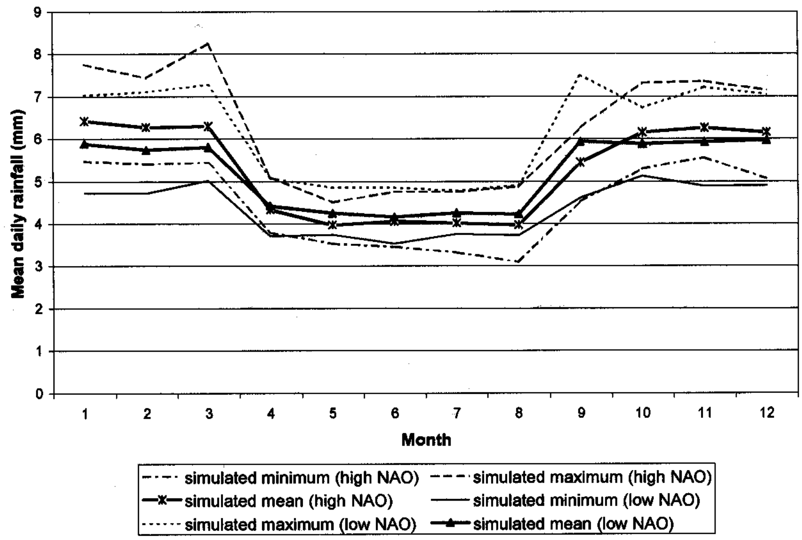

Fig. 11. *Mean daily rainfall for a high- and low-NAO scenario, with limits obtained from 50 simulations.*

This can be observed in Fig. 11. This approach provides a method of simulating the changes in the frequency of occurrence of weather states without the additional adjustment of internal precipitation model parameters.

Conclusions and possible further developments

A weather-type approach to precipitation modelling has been presented. Local precipitation characteristics were linked to larger-scale atmospheric circulation in the form of weather groups. A semi-Markov chain model was then developed to generate realistic sequences of daily weather states, based on the historical record. This was combined with the fitting of a stochastic NSRP model for each weather state that provides accurate simulations of historic statistics.

This model constitutes an improvement upon previous work in precipitation modelling for climate change assessment and the results of this paper may be summarised as follows:

1. The spatial distribution of precipitation in Yorkshire is strongly linked to atmospheric circulation patterns, and the region may be split into three zones of varying precipitation statistics.
2. Adequate spatial and temporal representation of the precipitation process is obtained by the use of just three weather states; 'westerly', 'northerly' and 'anticyclonic'.
3. The semi-Markov chain model requires the calibration of only three parameters per weather state in an automated process, for the accurate generation of synthetic weather state series.
4. NSRP model parameters can be easily estimated from historical data.
5. The model developed reproduces point precipitation statistics for each of the weather states in all three precipitation zones.
6. The conditioned model produces a significant explained variance in precipitation amount derived from weather states, when compared with an unconditioned model.
7. The methodology is flexible and transferable to other regions and can use the results of GCMs as a tool in climate change impact assessment.
8. It allows quantification of the effects of change in the frequency and persistence of weather states, but also instabilities within weather types, using long synthetic precipitation time-series.
9. Multi-site outputs of hourly precipitation are obtained which may be used for water resource management studies and other hydrological impact studies.

FUTURE POSSIBILITIES

The model presented in this paper is useful for a number of basic applications in water resource assessment. Some further evaluations and developments are necessary for the next stages in the application of the model in climate change impact assessments:

- To evaluate, or improve as necessary, the model capability of reproducing inter-annual variability of weather types and droughts of various return periods, concentrating on those events of crucial importance to water resource reliability.
- To explore the non-stationary nature of weather pattern versus rainfall conditioning using long precipitation

records to assess the stability and transferability of model parameters to future climate change scenarios. Presently, a constant baseline of 1961–1990 is assumed.

- To generate a range of future scenarios representing a plausible range of changes in weather type frequency and persistence.
- To apply the model outputs to a water resource model of the Yorkshire region to assess the possible impacts on system reliability and performance.

Acknowledgements

This work was undertaken as part of a Ph.D. thesis funded jointly by the Engineering and Physical Sciences Research Council (EPSRC) and the Environment Agency (North East Region). Precipitation data were supplied by Mike Stokes (York EA) and the British Atmospheric Data Centre, and LWT data by Phil Jones (Climatic Research Unit, UEA). Thanks are also due to Aidan Burton, who modified the NSRP rainfall modelling package, RainSim. The authors thank the reviewers for their helpful and detailed comments and, in particular, Phil Jones for discussions and advice.

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