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Assessing rainfall availability over the Sydney region in a future climate using stochastic downscaling

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Abstract: Coarse resolution of General Circulation Model (GCM) necessitates use of downscaling approaches for transfer of GCM output to finer spatial resolutions for climate change impact assessment studies. This paper presents an application of a stochastic downscaling framework for simulation of multi-site daily rainfall occurrences and amounts for the year 2070. The downscaling framework is developed using current climate reanalysis data and rainfall records at a network of 45 raingauge stations around Sydney in Australia, while information about the atmospheric variables of the CSIRO Mk3.0 GCM (corresponding to the SRES B1, A1B and A2 emission scenarios) is used for downscaling of rainfall for current and future climates. The model calibration and verification results for the baseline period (1960-2002) indicate that the proposed downscaling model simulates fairly accurately not only the standard rainfall attributes, such as the average number of wet days and rainfall amounts, but also rainfall extremes and the longer time scale variations and, therefore, can be used with confidence for assessing rainfall in a future climate.

Downscaled rainfall results for 2070 show large variations across the seasons and emission scenarios (Table 1). In general, wetter autumn and summer and drier winter and spring with regions along the coast getting wetter and inland regions becoming drier are projected. An increase of 2% by 2070 in annual rainfall is estimated. Amount per wet day also shows a minor increase of 4%. Increased instances of longer dry and wet spells with lighter rains are expected in future.

Table 1. Changes in seasonal and annual number of wet days and rainfall amounts in the year 2070. The median estimates are denoted as ME while percent changes in median, 5 and 95 percentile values are expressed as PC.

		Wet days changes in year 2070							Rainfall amount changes in year 2070					
		B1		A1B		A2			B1		A1B		A2	
Season	Current climate number of wet days	ME	PC in Median 5 95	ME	PC in Median 5 95	ME	PC in Median 5 95	Current climate rainfall amount in mm	ME	PC in Median 5 95	ME	PC in Median 5 95	ME	PC in Median 5 95
Autumn	28	32	+13.3 +17.8 +9.1	30	+6.6 +11.6 +2.2	29	+2.8 +7.1 -2.3	238	297	+24.9 +40.8 +12.0	266	+11.8 +20.5 +3.0	242	+1.7 +9.7 -5.8
Winter	25	23	-10.9 -6.1 -15.1	23	-10.1 -6.0 -13.5	23	-8.6 -4.4 -12.6	195	177	-9.3 +2.9 -19.9	190	-2.6 +10.6 -12.2	178	-8.5 +3.5 -19.2
Spring	28	28	-1.6 +2.7 -5.8	26	-8.4 -3.8 -12.5	26	-6.8 -1.8 -11.3	235	249	+6.3 +17.4 -3.5	207	-11.7 -4.0 -18.8	221	-6.0 +3.5 -15.4
Summer	30	32	+6.4 +10.9 +1.8	28	-7.0 -2.9 -11.7	31	+2.9 +7.0 -1.4	284	329	+16.0 +24.6 +7.5	265	-6.5 +1.4 -14.1	314	+10.5 +21.8 -0.1
Annual	111	113	+1.5 +4.4 -1.3	106	-5.4 -2.5 -8.4	109	-2.6 +0.3 -5.7	951	1040	+9.4 +15.9 +5.0	919	-3.4 +0.8 -7.7	946	-0.5 +4.8 -5.7

Keywords: *Multisite rainfall, stochastic downscaling, modified Markov model (MMM), kernel density estimation (KDE)*

1. INTRODUCTION

General circulation models (GCMs) are among the most advanced tools used to simulate the present climate and to obtain detailed climate information needed for the assessment of the various consequences of future climate changes on ecosystems and societies, both in space and in time (e.g. IPCC, 2007; Bergström et al., 2001; Varis et al., 2004). The GCMs are usually run at coarse-grid resolution and provide a reasonably accurate representation of the average planetary climate. However, they are incapable of representing local sub-grid-scale features and dynamics that are often required for impact studies (IPCC, 2007; Charles et al., 2004; Vicuna et al., 2007). As a consequence, techniques have been developed to transfer the GCM output from the large spatial scales to the local or regional scales by means of downscaling for use in catchment modelling studies. Statistical downscaling is thus a way to infer local information from coarse-scale information by applying empirical or statistical links between large-scale fields and local conditions. Such statistical links may be used both to validate global and regional climate models and to develop detailed local climate scenarios based upon the output from such climate models. A diverse range of statistical downscaling techniques have been developed over the past few years, with regression-based and weather state-based methods being quite popular. Charles et al. (2004), IPCC (2007) and Fowler et al. (2007) provide excellent reviews and discussions of various downscaling techniques.

This paper presents a downscaling framework that is capable of simulating the observed common rainfall features as well as the low frequency variability in the simulated rainfall field. The framework operates in two stages: first the downscaling of rainfall occurrences and thereafter of the rainfall amounts on the simulated wet days. The rainfall occurrence downscaling model is an extension of the Modified Markov Model (MMM) (Mehrotra and Sharma, 2007). The model conditionally simulates the occurrence field based on exogenous atmospheric forcings and aggregated longer time scale variables that represent the low frequency variability of rainfall within the commonly used Markov order one dependence structure. At-site rainfall amounts on wet days are simulated using a kernel density estimation based approach (hereafter referred to as KDE) that allows proper representation of temporal dependence attributes. Spatial correlation of rainfall occurrence and amounts is maintained by making use of random innovations that are spatially correlated yet serially independent in nature (Wilks, 1998). The smooth transition from one season to another is made possible by using the concept of a moving window (Harrold et al., 2003; Mehrotra and Sharma, 2005). The downscaling framework is initially calibrated using reanalysis atmospheric data and observed daily rainfall (1960-2002) at 45 raingauge stations located around Sydney, Australia, and thereafter validated using current climate GCM data. Finally, the model is applied to downscale daily rainfall for the year 2070 and changes in rainfall behaviour evaluated.

2. METHODOLOGY

In the discussions that follow, all multivariable vectors or matrices are expressed as bold and single variables or parameters using non-bold characters or symbols. We denote rainfall occurrence at a location *k* and time *t* as $R_t(k)$. Also, a n_s-site rainfall vector at time *t* is denoted as $\mathbf{R}_t$ and a vector of predictor variables (consisting of atmospheric and/or other relevant indicators) as $\mathbf{Z}_t$. Unless explicitly specified, hereafter the term rainfall represents rainfall amount. The following describe the rainfall occurrence and amount models.

2.1. Downscaling of Rainfall Occurrence using MMM

In the following discussions, we present the parameterization scheme of the conditional simulation of $\mathbf{R}_t(k)|\mathbf{Z}_t(k)$. For brevity, site notations are dropped in the subsequent discussions. The parameters (or the transition probabilities) of a stochastic model expressing the order one Markovian dependence (first order Markov model) are defined by $P(R_t|R_{t-1})$ with $\mathbf{Z}_t$ consisting of R_{t-1} only. Inclusion of additional continuous predictors $\mathbf{X}_t$ in the conditioning vector $\mathbf{Z}_t$ would modify these transition probabilities as $P(R_t|R_{t-1},\mathbf{X}_t)$. The following parameterization is adopted to estimate $P(R_t|R_{t-1},\mathbf{X}_t)$:

$$P(R_t=1|R_{t-1}=i,\mathbf{X}_t)=\frac{P(R_t=1,R_{t-1}=i,\mathbf{X}_t)}{P(R_{t-1}=i,\mathbf{X}_t)}=\frac{f(\mathbf{X}_t|R_t=1,R_{t-1}=i)\times P(R_t=1,R_{t-1}=i)}{f(\mathbf{X}_t|R_{t-1}=i)\times P(R_{t-1}=i)}=\frac{P(R_t=1,R_{t-1}=i)}{P(R_{t-1}=i)}\times\frac{f(\mathbf{X}_t|R_t=1,R_{t-1}=i)}{f(\mathbf{X}_t|R_{t-1}=i)}$$
$$=\frac{P(R_t=1,R_{t-1}=i)}{P(R_{t-1}=i)}\times\frac{f(\mathbf{X}_t|R_t=1,R_{t-1}=i)}{[f(\mathbf{X}_t|R_t=1,R_{t-1}=i)P(R_t=1|R_{t-1}=i)]+[f(\mathbf{X}_t|R_t=0,R_{t-1}=i)P(R_t=0|R_{t-1}=i)]} \quad (1)$$

The first term of (1) defines the transition probabilities $P(R_t|R_{t-1})$ of a first order Markov model (representing order one dependence), while the second term signifies the effect of inclusion of predictor set $\mathbf{X}_t$ in the conditioning vector $\mathbf{Z}_t$. If $\mathbf{X}_t$ consists of derived measures (typically linear combinations) of atmospheric variables and/or summation of number of wet days in pre-specified aggregation time periods (as explained later in sub-section 3.2), one could approximate the associated conditional probability density $f(\mathbf{X}_t|R_t=1,R_{t-1}=i)$ as a multivariate normal. However, when dealing with many atmospheric variables, the assumption of a multivariate normal may not be appropriate, as is found in the present study. In such situation, the conditional multivariate probabilities $f(\mathbf{X}_t|R_t=1,R_{t-1}=i)$ and $f(\mathbf{X}_t|R_t=0,R_{t-1}=i)$ of equation (1) may be estimated using nonparametric kernel density estimation procedure. In order to save computer time, the switching from parametric to non-parametric multivariate density estimation at each time-step is decided on the basis of average skewness of the data set $\mathbf{X}$ (if skewness < 0.3 then parametric, otherwise nonparametric, density estimation procedure is implemented).

2.2. Downscaling of Rainfall Amounts

A nonzero rainfall amount (a rainy day is defined using a threshold of 0.3 mm/day) must be simulated for each day at each location that the MMM occurrence downscaling model simulates as wet. The downscaling of rainfall amount is based on the kernel density procedure. It downscales the rainfall at individual stations conditional on selected atmospheric variables as well as the previous day's (or days') rainfall. Further details on the general structure of the KDE model are available in Mehrotra and Sharma (2007).

2.3. Modeling Spatial Dependences in Rainfall Occurrence and Amounts

As discussed above, stochastic downscaling of rainfall occurrences or amounts for a given location proceeds through simulation from the associated conditional probability (or transition probability) distribution, each value of a realization being generated based on an independent uniform (0,1) random variate. The rationale used to incorporate spatial dependence in such simulations over many point locations involves using uniform random variates that are independent in time but exhibit a strong dependence across the multiple point locations considered. More details on this rationale are available in Wilks (1998) and Mehrotra et al. (2006).

3. APPLICATION OF DOWNSCALING MODEL

3.1. Datasets, Study Area and Variables

Study area, rainfall and large scale atmospheric variables

The study region is located around Sydney, eastern Australia spanning between 149°E - 152°E longitude and 32°S - 36°S latitude (Figure 1). The physio-geographical conditions in the Sydney region cause large climatic gradients even over short distances, e.g. from lowland areas to mountain regions and from the coast to the inland. For this study, a 43-year continuous record (from 1960 to 2002) of daily rainfall at 45 stations around Sydney (Figure 1) was provided by the Sydney Catchment Authority (SCA). The required observed atmospheric variables for 25 grid points over the study area are extracted from the National Center for Environmental Prediction (NCEP) reanalysis data provided by the NOAA-CIRES Climate Diagnostics Centre, Boulder, Colorado, USA, from their web site at http://www.cdc.noaa.gov/. Runs of Commonwealth Scientific and Industrial Research Organisation (CSIRO), Australia Mark3 GCM (Gordon et al. 2002) for the three emission scenarios SRES B1, A1B and A2 (IPCC 2007) are considered in the present study. GCM datasets of atmospheric variables for the baseline (covering a 43-year period between 1960 and 2002 and representing the current climate) and for the year 2070 (2061–2080) periods are considered in the analysis.

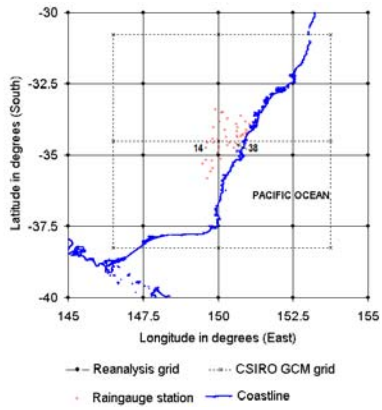

Figure 1. Reanalysis and CSIRO GCM data grids and study region.

Adjustment of GCM data

Some scaling is required to be carried out on the GCM data to remove the regional biases without affecting the climate change signal (shift from the current climate to the future). We adjust the GCM data for the baseline (1960-2002) and future climate period (2061-2080) by adopting a two-stage adjustment procedure.

In the first stage, the GCM series (current and future climates) is corrected for bias in the mean by subtracting the mean of the baseline period GCM data and adding the mean of the baseline period reanalysis data. In the second stage, the mean-corrected GCM series (for current and future climates) is rescaled to correct for bias in standard deviation without affecting the mean.

Identification of significant predictors

On the basis of the results of earlier downscaling studies (Mehrotra and Sharma 2005; Charles et al., 2004), we choose a large set of atmospheric predictors comprising of circulation and moisture variables at various levels and their horizontal and vertical gradients as the potential predictors. A nonparametric stepwise predictor identification analysis based on partial mutual information (Sharma, 2000) is carried out to identify sets of significant atmospheric predictors for each season (MAM, JJA, SON, DJF) and for occurrence and amounts models. Current climate reanalysis data at 25 grids points (interpolated to 9 GCM grids points) covering the study area (Figure 1) is used in calculating the area averaged value and gradients. Table 2 presents the list of identified significant predictor variables for each season and occurrence and amount processes.

Table 2. Identified seasonal large scale atmospheric variables used in rainfall occurrence and amount downscaling.

Seasons	Rainfall occurrences	Rainfall amounts
Autumn	Temperature depression at 700 hPa	Temperature depression at 700 hPa
	NS gradient of geopotential height at 850 hPa	NS gradient of geopotential height at 850 hPa
	Vertical velocity at 850 hPa	Vertical velocity at 500 hPa
	Vertical velocity at 500 hPa	Vertical velocity at 850 hPa
Winter	Temperature depression at 700 hPa	Temperature depression at 700 hPa
	NS gradient of geopotential height at 850 hPa	NS gradient of geopotential height at 850 hPa
	Vertical velocity at 850 hPa	Gopotential height at 850 hPa
	Vertical velocity at 500 hPa	Vertical velocity at 850 hPa
Spring	Temperature depression at 700 hPa	Temperature depression at 700 hPa
	NS gradient of geopotential height at 850 hPa	Temperature depression at 850 hPa
	Temperature depression at 850 hPa	Vertical velocity at 500 hPa
	500 -1000 hPa thickness of vertical velocity	Vertical velocity at 850 hPa
Summer	Temperature depression at 700 hPa	Temperature depression at 700 hPa
	NS gradient of geopotential height at 850 hPa	Temperature depression at 850 hPa
	Temperature depression at 850 hPa	Vertical velocity at 500 hPa
	Vertical velocity at 850 hPa	Vertical velocity at 850 hPa

3.2. Selection of Model Parameters

For rainfall occurrence downscaling model (MMM), we consider individual at-site Markov order one models conditional on pre-identified atmospheric variables (common across all stations) and previous 365 days (at individual site) wetness state (on any given day, number of wet days in previous 365 days divided by 365). To improve the representation of area averaged wetness fraction, previous day's area averaged wetness fraction (for the localised region) is also included as a conditioning variable. The conditioning vector considered for downscaling of rainfall amount at a station thus includes pre-identified atmospheric variables for each season, previous day rainfall and a variable defining the local wetness density.

4. MODEL RESULTS

In all the results that follow, the statistics reported are ascertained by simulating 100 realisations of the downscaled rainfall from the model. As all emission scenarios for current climate exhibit similar performances, in order to save the space results of only one emission scenario are presented and these are mentioned hereafter as 'GCM current climate'. Please note that the results presented for changes in the future climate are compared with the GCM current climate.

Table 3. Observed and model simulated mean number of wet days and rainfall totals with 5 and 95% probability limits for the current climate (1960-2002).

Season	Number of wet days			Rainfall amounts in mm		
	Observed	Simulated using		Observed	Simulated using	
		Reanalysis data	GCM data		Reanalysis data	GCM data
Autumn	28	27(26-27)	28(27-29)	266	273(256-291)	238(223-253)
Winter	26	26(25-26)	25(25-26)	210	212(196-230)	195(182-209)
Spring	29	29(28-29)	28(27-29)	230	246(235-264)	235(222-246)
Summer	30	29(28-30)	30(29-31)	280	285(269-302)	284(270-298)
Annual	112	110(109-113)	111(109-114)	986	1016(989-1047)	951(918-981)
Annual standard deviation	15	19(18-21)	14(13-16)	259	280(251-313)	214(185-241)

4.1. Model Calibration and Verification Results for the Baseline Period

Number of wet days

Table 3 compares the observed and downscaled seasonal and annual wet days and rainfall averages over the study region. The model accurately reproduces the overall spatial distribution of rainfall occurrences and amounts over the study area for all seasons and year during calibration (using reanalysis data) and verification (using reanalysis data) stages.

Other rainfall extremes statistics

The downscaling model also reproduces successfully the distribution of observed at site and area averaged annual rainfall occurrences and amounts, longer durations wet and dry spells and rainfall extremes. Figure 2 presents a few of these results at all raingauge stations used in the study.

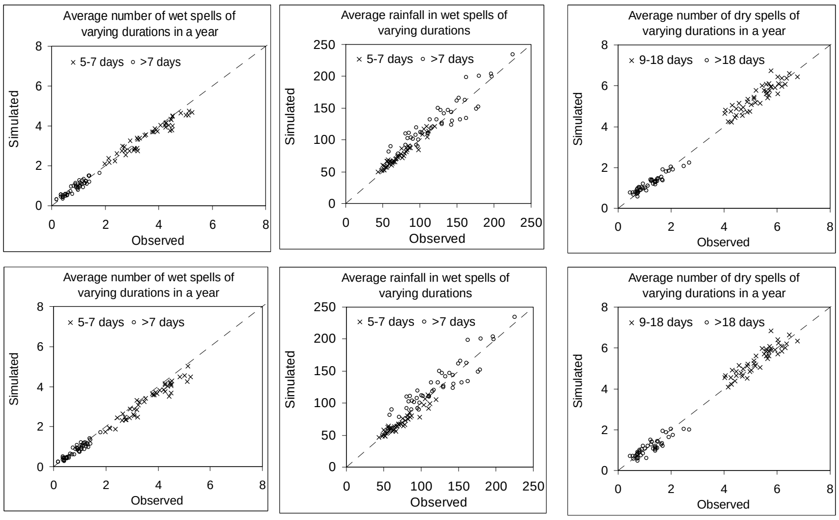

Figure 2. Observed and model simulated average number of wet and dry spells of varying durations for current climate using reanalysis (top row) and GCM (bottom row) datasets. Symbols on the plots indicate raingauge stations used in the study.

4.2. Model Results for 2070

For a majority of statistics analysed, climate projections show wide variations across the scenarios and seasons. All emission scenarios are assigned equal weightage in the analyses presented in the subsequent sections.

Projected rainfall changes

The details on the best estimates of the projected percent changes in the rainfall amount on seasonal and annual basis in the year 2070 are presented in Figure 3 and Table 1. By 2070, under B1 scenario, the range of annual wet days change is -1.3 to 4.4% with median best estimate of 1.5% increase, while for annual rainfall the change is from +5 to +15.9% with median best estimate of 9.4% increase. Both A1B and A2 scenarios project slight decreases in annual number of wet days and rainfall amount. For A1B the decrease is -5.4% (range -8.4 to -2.5%) for wet days and -3.4% (range from -7.7 to 0.8%) for rainfall amount, while the corresponding figures for A2 are -2.6% (range -5.7 to -2.6%) and -0.5% (range -5.7 to +4.8%) respectively. Collectively, by 2070 the range of annual wet days change is -8 to 4% with 2% decrease and of annual rainfall is -8 to 16% with 2% increase.

Daily rainfall intensity, wet and dry spells and extreme rainfall

Results of projected changes in per wet day rainfall amount in the year 2070 are analysed at annual level. In general, north-east part of the study area is expected to get a slight increase (5%) in per wet day rainfall, while west and south-west parts experience a slight decrease (-5%) in per wet day rainfall. An increase (about 4%) in daily rainfall intensity (rain per wet day) with B1 scenario projecting a maximum increase of 7.7% is estimated. The distribution of daily rainfall and spells extremes over the study region are presented in Table 4. It may be noted that these events, being of rare nature, show higher variability and hence more uncertainty in the projected changes. The number of days in a year with extreme rainfall over the region (greater than 40 mm/day) is likely to decrease. Wet spells of 5-6 days are expected to increase in autumn and summer and decrease in winter and spring with an increase of 17% (-69 to 159%) at annual level. Rainfall amount in these spells is likely to increase in autumn, spring and summer and decrease in winter. Also, increased instances of wet spells of 7 days or more (probably with light rain) are projected more specifically along the coastal areas.

The increased frequency of occurrence of longer wet spells is mainly expected to occur in autumn and summer. Rainfall amount in these longer wet spells is likely to increase in autumn and decrease in summer. Increased frequency of occurrence of longer dry spells (of 15 days or more) is also estimated in the future. The increased frequency of wet spells with likely decrease in wet spell rainfall, increased frequency of dry spells and slight increase in total rainfall suggest that the future rainfall regime will have longer dry spells interrupted by heavier rainfall events.

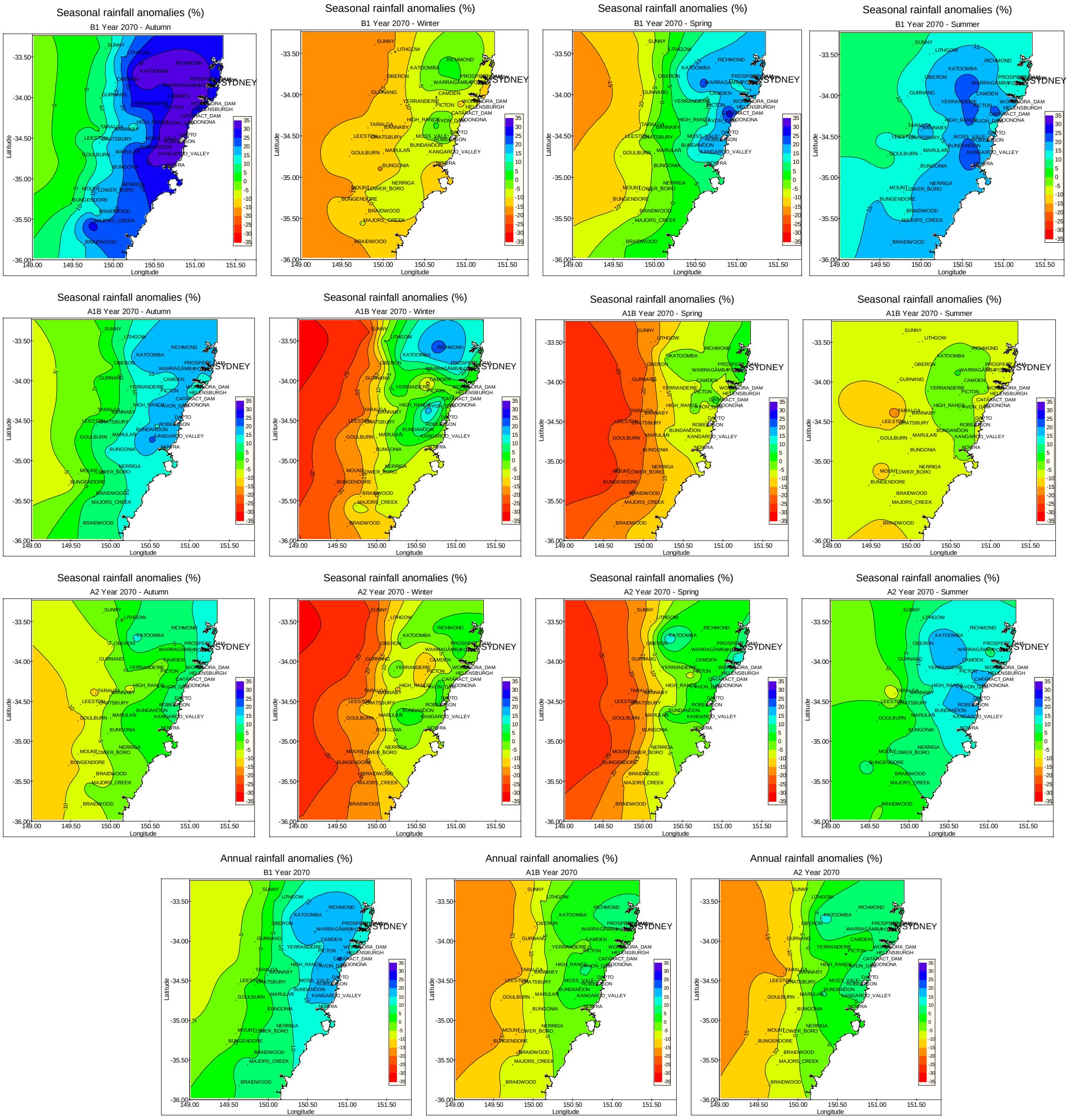

Figure 3. Seasonal and annual rainfall anomalies expressed as a percentage difference of model simulated and current climate rainfall for year 2070 and for B1, A1B and A2 scenarios.

5. SUMMARY AND CONCLUSIONS

This paper has demonstrated the calibration, verification and application of a relatively simple stochastic downscaling framework for multi-site rainfall simulation using current and future climate atmospheric information. The novelty of the downscaling approach proposed here is its capability in simulating the observed low frequency variability in the downscaled simulations.

The model calibration and verification results for the baseline period (1960-2002) indicate that the downscaling model proposed here simulates fairly accurately not only the standard rainfall attributes, such as the average number of wet days and rainfall amounts, but also maximum daily rainfall amount, extended periods of wet and dry spells and the longer time scale variations.

The model has been applied to get the downscaled rainfall for 2070. Downscaled results show broad variations across the seasons and emission scenarios. In general, wetter autumn and summer and drier winter and spring with regions along the coast getting wetter and inland regions becoming drier are projected. An increase of 2% in annual rainfall is estimated. Amount per wet day also shows a minor increase of 4%. Increased instances of longer dry and wet spells with lighter rain are expected in future.

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Table 4. Percent changes in annual occurrence of extreme rainfall attributes in year 2070.

Rainfall attribute	Average annual occurrence in current climate	Percent change in year 2070		
		5th percentile	Median	95th percentile
Days with 95 percent of stations receiving rainfall	26	18	-2	-15
Days with area averaged rainfall>40 mm	1.5	20	-28	-64
Days with 90 percent of stations receiving rainfall and this condition has persisted for 5-6 days	0.33	159	17	-69
Days with all stations are dry and this condition has persisted for >14 days	0.06	82	16	-27

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