Climate Change Scenarios for New Zealand Rainfall

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ABSTRACT

In terms of the effects of future climate change upon society, some of the most important parameters to estimate are associated with changing risks of extreme rainfall events, both floods and droughts. However, such aspects of the climate system are hard to estimate well using general circulation models (GCMs)—in particular, for a small mountainous landmass such as New Zealand. This paper describes a downscaling technique using broad-scale changes simulated by GCMs to select past analogs of future climate. The analog samples are assumed to represent an unbiased sample of future rainfall and are used to develop detailed descriptions of rainfall statistics using hidden semi-Markov models of rainfall breakpoint information. Such models are used to simulate long synthetic rainfall time series for comparison with the historical record. Results for three New Zealand sites show overall increases in rainfall with climate change, brought about largely by an increased frequency of rainfall events rather than an increase in rainfall intensity. There was little evidence for significant increases in high-intensity short-duration rainfalls at any site. Such results suggest that, although regional increases of rainfall are consistent with expected future climate changes, it may be that circulation changes, rather than temperature (and vapor pressure) changes, will be the more important determinant of future rainfall distributions, at least for the coming few decades.

1. Introduction

a. Background

Expected average increases in global mean temperature during the twenty-first century have been assessed to lie between 1.4° and 5.8°C, relative to 1990 levels (Cubasch et al. 2001). In global terms, the hydrological cycle is expected to increase in intensity with rising temperatures. All general circulation model (GCM) simulations used in the last Intergovernmental Panel on Climate Change assessment of climate change (Cubasch et al. 2001) show an increase in global mean precipitation through the twenty-first century. The rate of increase is around 3%–4% per degree of warming, or about one-half of the theoretical maximum increase. Less well defined are expected regional changes in rainfall and changes in short-duration or extreme rainfalls.

Rainfall scenarios from GCMs depend upon the details of the physical parameterizations used in the cloud and surface energy exchange components of the model. Hence, different models show different rainfall futures at the regional scale, even if their mean surface temperatures agree well (Whetton et al. 1996). The more local the spatial scale of comparison is, the more disagreement is likely. Moreover, most decision makers and policy makers are particularly interested in the changes in duration and frequency of extreme rainfalls rather than in changes in mean amounts. Although GCMs do a good job of simulating the pattern of present-day mean rainfall globally, they exhibit less skill in modeling extremes of rainfall (Kiktev et al. 2003; Renwick et al. 1998) and hence may be somewhat unreliable in terms of estimating future changes in the tails of rainfall distributions.

One approach to such problems is to employ downscaling techniques that explicitly take account of the distribution of present-day rainfall and that incorporate ways of estimating future changes in extremes as a function of changes in regional or global mean rainfall, temperature, and other climate statistics (e.g., Benestad 2004; Charles et al. 2004; Murphy 1999; Semenov and Bengtsson 2002). This paper describes such an approach that uses a statistical model of rainfall forced by mean changes derived from GCM future climate simu-

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lations. The strength of the statistical approach used here is the strong focus on the estimation of short-duration rainfalls through the use of breakpoint rainfall data and the hidden semi-Markov model (HSMM) framework.

b. Climate change scenarios for New Zealand

A number of coupled ocean–atmosphere GCM simulations were evaluated recently for the New Zealand region and were used in a statistical downscaling study for the New Zealand landmass (Mullan et al. 2001). The GCM parameters of importance were regionally averaged surface temperature, rainfall, and zonal/meridional wind components. The latter were used because regional variation in the surface climate of New Zealand is largely a result of the interplay between the mean westerly circulation and the significant orography that lies almost directly across its path (Sturman and Tapper 1996).

The consensus among the GCMs analyzed was for a gradual increase in westerly wind strength across New Zealand, as a result of the relatively slow warming of surface waters in the southern oceans in comparison with the more rapid warming of subtropical waters. Such a circulation trend would act to slow temperature rises in western regions and accelerate them to the east, in the lee of the main mountain chains (Mullan et al. 2001).

Estimated temperature changes over New Zealand, assuming future emissions close to the Special Report on Emissions Scenarios A1 scenario [Nakicenovic and Swart (2000); a "midrange" scenario featuring substantial future economic growth but with relatively rapid implementation of alternative energy technologies (see information online at http://www.grida.no/climate/ipcc/emission/)], were on the order of 75% of estimated changes in the global mean, being around 0.7°C in the 50 yr to 2040 and another 1°C or so in the following 50 yr. As noted above, increases are expected to be larger in eastern regions. The overall change in precipitation in the New Zealand region was near zero, averaged across models, but the increased westerly wind flow implies an increase in mean rainfall in western regions and a decrease in the east, with the magnitude of the change being strongly related to the modeled change in westerly wind strength.

In this paper, such projected changes are used to sample selectively the historical record for past conditions that may be analogous to mean New Zealand conditions approximately 50 yr in the future. Months from the historical record that were generally warm over the country and that exhibited enhanced westerly wind strength were extracted for detailed analysis of their rainfall. The expectation was that such an analog approach should provide useful information on local spatial scales about extreme rainfall behavior that is not available directly from GCM output. Given that the basic physics of the atmosphere can be considered invariant, warm and windy periods from the past should serve as reasonable proxies for typical climate conditions in the future, provided there are no large changes in regional climate variability. Support for the validity of this idea comes from the GCM results mentioned above, which show little overall change in total rainfall in the New Zealand region, suggesting that the current mix of rain-bearing weather systems is not likely to change significantly over the coming few decades. Further, as will be shown later, the past analogs available for study more than span the range of expected 50-yr changes in mean temperature and windiness over New Zealand. Study of high-resolution rainfall records during those past analog periods should therefore give useful insights into expected future changes in rainfall and its extremes, in particular.

The validity of such insights rests largely on the assumption that the use of analog data is valid and, second, on what strategy is used in selecting that data from what is available. Support for the basic assumption has been given above, but counterarguments can be advanced. A primary one is that, despite the basic physics being invariant, the potential exists for climate processes to change so that, for example, changes in circulation patterns could increase the frequency of storms of tropical origin affecting New Zealand, especially northern areas. Representation of this increase might not be achieved within the analog dataset either because it is not possible from the range of available data or because the selection strategy is inadequate. These possibilities would also apply to any other climate changes and, although nothing can circumvent the first possibility because the amount of data is limited, a range of selection strategies can be envisaged. At the outset it seemed important to use a strategy that included as many of the warm and windy periods as possible to avoid the criticism that a result indicating small changes arose from ignoring the extreme cases. Such a strategy, which provides a worst-case scenario, was used and was only able to provide a single analog dataset, and therefore the potential of a sampling bias exists. However, the same potential exists for any selection strategy, and the overarching assumption becomes not just that the use of analog data is valid but that the application of the chosen selection strategy yields an unbiased sample of future rainfall.

c. Data analysis approach

The next section describes how the analog period was constructed and is followed in section 3 by a comparison of the current rainfall climate with that of the analog period. To facilitate this comparison, the idea of capturing the character of rainfall in a statistical model of high-temporal-resolution (about 1 min) rainfall data is used by fitting models to datasets from the recent past and from the analog period. The high-resolution data are called *breakpoints* (Sansom 1992; Barring 1992), and they have been modeled as HSMMs (Sansom 1999; Sansom and Thompson 2003).

Breakpoints are described in more detail in section 4. They provide high-temporal-resolution data in a compressed and physically based way by recording the times of significant changes in the rain rate that result from changes in the drop size distribution (DSD) of the raindrops. A steady rain rate, which can be called the *ambient* rate (Sansom and Thompson 2003), lasts for an arbitrary time between such DSD changes. Thus, the breakpoint dataset consists of the sequence of steady rain rates and the times of its change or, equivalently, the levels and durations of the steady rain rates with dry times included as periods with a zero rain rate. The value of breakpoints with regard to climate change is motivated by the following:

1) Rain generation takes place over a wide range of spatial scales from that in a frontal system to that in small convection cells. The temporal scales for rainfall events (a definition of *event* is offered in section 4) are equally wide, with frontal systems lasting days but convection cells lasting a few hours at most.
2) Within most rainfall events, the rate of rainfall varies frequently in response to changes in atmospheric dynamics and the supply of moisture, and it is these drivers that will be affected by climate change.
3) For climate change effects on rainfall, it is the shorter temporal scales that are important because, although accumulations over days, or even hours, do result from shorter-time-scale activity, they are unlikely to contain sufficient information to capture the effect of climate change.
4) Thus, high temporal resolution of rainfall is required to resolve any changes in the characteristics of rainfall.

Some options that can be taken in the fitting of HSMMs to emulate some of the ways in which climate change might affect rain-generating mechanisms are described in section 5. The changes in the rainfall climate that occur under the various scenarios are discussed in section 6. The final section provides a summary and some conclusions.

2. Selecting the analog period

The stations chosen for detailed analysis were Auckland in the north of New Zealand at 36°48′S, 174°36′E; Wellington in central New Zealand at 41°17′S, 174°46′E; and Invercargill in the far south of New Zealand at 46°25′S, 168°20′E. All of these places have long and complete sets of pluviographs covering much the same period as that of the temperature and wind indices. The pluviographs for the years since 1986 were available as manually digitized breakpoint datasets, and those months from earlier years that were selected for the analog period were specially digitized for this study.

To represent the future, an analog period with a length of several years was constructed by selecting from a recent 44-yr period those months that, individually, were thought to resemble most what is expected in the future. The selection was made on the basis of two indices, both of which had monthly values available for the period from January 1950 to December 1993 (and later, but Auckland rainfall data were not available after that time). The temperature index is simply the departure of the national mean temperature from its mean over the 1961–90 period. The westerly index is the Trenberth Z1 index (Trenberth 1976), which is the departure of the monthly mean pressure difference between Auckland and Christchurch (near 44°S) from its mean over the 1961–90 period.

At least 5 yr of data are required to obtain reliable estimates of the HSMM parameters and to sample adequately the rainfall climate. Not just any 60 months were selected, but rather five Januarys, five Februarys, and so on were taken to capture seasonality and interannual variability. Preserving some degree of seasonality in that way also handled correlation on monthly time scales that arises mainly from seasonality (Sansom and Thomson 2007), but it did effectively reduce the range of choice. Appendix A presents a short analysis of month-to-month correlations in the various datasets used in this paper.

Figure 1 shows the scatterplot of one index against the other. If only the warming aspect of climate change was to have been considered then the warmest months could be chosen by picking the months that are on the right-hand side of the scatter. In a similar way, for just the increase of westerlies the months at the top of the scatter would be chosen. However, the relative importance of the two factors is not known, and the selection strategy was to give them equal weight by scaling the scatterplot to give a “round” cloud of points to conform with the low correlation (0.11) between the two indexes and then drawing a slope -1 line such that above it

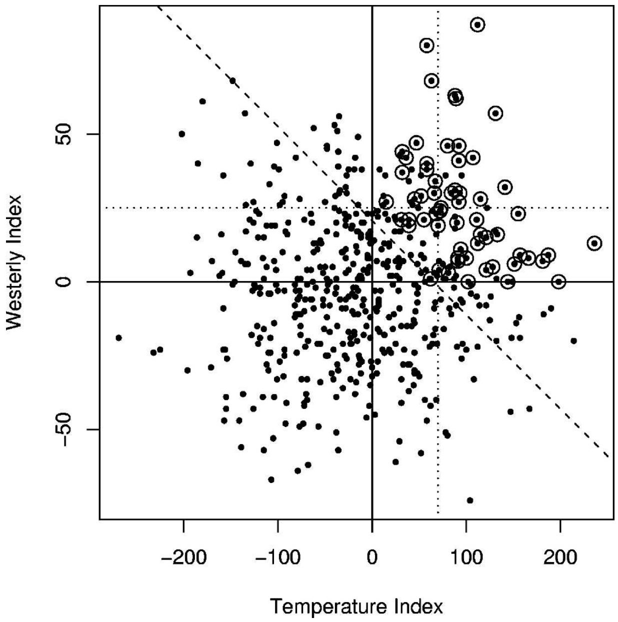

FIG. 1. Scatterplot of the anomaly of the monthly mean national mean temperature against the Trenberth Z1 index of westerly strength. The period covered is January 1950–December 1993. The dashed line is at an angle of 45°, and months chosen as the analog period are circled. The expected positions of the axes in about 2050 are shown by the dotted lines.

there were at least five cases for each month (the limiting month was December for which only five with matching breakpoint data lie above the line); the 109 points thus selected gave more-than-adequate scope, apart from December, for selecting 60 to form the 5-yr analog period.

The 60 months were arranged into a sequence starting with a January, followed by a February, and so on such that no year in the analog period contained months from the same actual year and successive Januarys, Februarys, and so on were not from actual successive years. This was not quite achieved, mainly because of all the months from June to December of 1988 being included in the candidate set, but a set was found for which the only exception was that for one of the analog years August, November, and December were all from 1988. The months selected have been circled in Fig. 1 in which it can be seen that most of the months with the most positive temperature and westerly indexes were included in the analog period. Those not included were mainly relatively close to the slope −1 line. Figure 1 also shows where the axes of the scatter are expected to lie in 2050 according to typical GCM results (Mullan et al. 2001) and indicates that the selected months were centered approximately on the new origin.

3. Initial assessment of current and analog rainfall climates

Four statistics to represent the rainfall climate were selected. To cover both mean and extreme conditions, the total annual accumulation and the annual 12-h maximum were selected. These statistics will be referred to as the "Total" and "Max," respectively. For describing the intermittency of rainfall, the annual number of 1-mm wet days (the number of days that received at least 1 mm of rain) was chosen. For capturing extreme conditions in intermittency, the annual maximum dry spell (i.e., the longest period of days during which each of the days was not a 1-mm wet day) was chosen. These statistics will be referred to as "WetDays" and "DrySpells," respectively.

Figure 2 shows box plots of these four statistics with a panel for each statistic–station combination. Each panel contains a box plot for the "Long Term" dataset, another for a 5-yr period in the recent past that will be referred to as "Now," and a third for the 5-yr period constructed in the previous section, which will be referred to as "Future". The Now dataset was introduced to provide comparisons with the Future dataset free from the effects of sample size, such as can be seen in Fig. 2 in the qualitative difference between the Long-Term box plots and the others. More important, because, as will be described in section 5, the assessment of the Future dataset was to be through HSMM simulations, current conditions should also be assessed through HSMM simulations to ensure that, despite any model biases, valid comparisons with the Now dataset can be made. The period chosen for Now was 1988–92 because, from all of the available continuous 5-yr periods, its box plots were most similar to the Long-Term ones.

A box plot is a visual summary of a dataset's distribution that shows its median as a line through a box that extends from the lower to the upper quartile. Whiskers extend from the box as far as the most extreme data point that does not lie more than 1.5 times the interquartile range from its nearest quartile; more extreme points are plotted individually and may be considered to be outliers. The notch in the box is centered on the median and represents a 95% confidence interval for the median. Thus, when comparing box plots, if the notches do not overlap then the medians are significantly different at the 5% level.

With only five points available for the Now and Future box plots, the medians are not well defined, with their confidence intervals often extending beyond one or both of the quartiles to give a "folded back" appearance to the interquartile box. They tend to have much

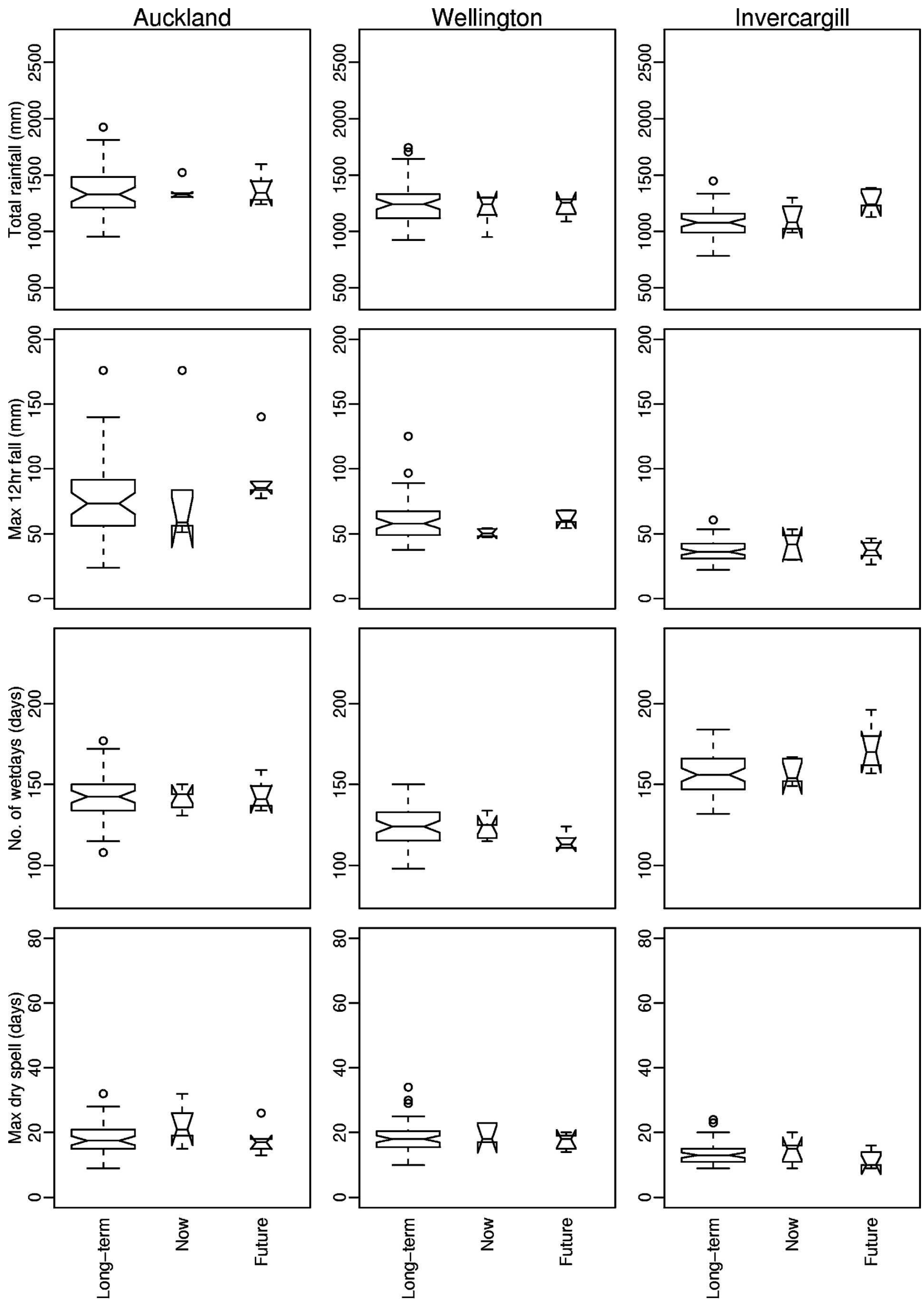

FIG. 2. Box plots for the annual statistics (Total, Max, WetDays, and DrySpells) at (left) Auckland, (middle) Wellington, and (right) Invercargill. In each panel, a box plot is given for the whole period that the station has been observing (Long Term), for a 5-yr period in the recent past (Now), and for the analog period (Future).

wider notches than the Long-Term ones to the extent, in general, that the notches of all three overlap. Thus, at the 5% level, the medians are not significantly different, implying that the rainfall climate is not expected to change. There are only two exceptions, that is, at Wellington the WetDays statistic decreases and at Invercargill Total increases, but only with respect to Long Term and not to Now. However, as might be expected, climate change cannot be seen given only two 5-yr periods from which a small number of rainfall statistics are extracted in the most straightforward way. In essence, whatever the actual progress of rain with time during these periods, it was summarized as either daily or 12-h accumulations, which ignores much of the information available in the rainfall breakpoints. As outlined in section 1, the changes and durations of the rate of rainfall characterize rainfall and can only be captured by a more detailed summary of these 5-yr periods, such as is available in the parameters of an HSMM fitted to each period.

4. Hidden semi-Markov models of breakpoint data

The controlling parameters of the process that produces a stationary DSD are summarized within the breakpoint data through the ambient rain rate associated with each DSD (Marshall and Palmer 1948; Joss and Waldvogel 1969; Torres et al. 1994). In essence, certain conditions prevail for some interval within the precipitation-generating mechanism (PGM), a stationary DSD is maintained through that interval, the overall effect is an ambient rain rate, and breakpoint data capture the ambient rates and their durations. Several PGMs are needed to cover convective and frontal rain, plus a null PGM when precipitation is not possible (Sansom and Thompson 2003).

This approach implies for rainfall a hierarchical division of time with three levels, that is, 1) durations of stationary DSDs or the breakpoint data themselves, which can be termed the wet or dry durations, or simply the "wets" or "drys"; 2) durations of PGMs consisting of a series of DSDs, and together composing an "episode"; and 3) a sequential series of PGMs, which together compose an "event," with the null PGMs being the interevent drys. The hierarchy is illustrated schematically in Fig. 3 in which one event from the top timeline has been expanded on the second timeline into a series of four PGM episodes. The breakdown of the PGMs into DSDs is shown on the third timeline where "w" and "d" indicate wet and dry breakpoint periods, respectively. The duration of the breakpoints is shown in the figure as a section of the timeline, and a rain rate is associated with each duration, with the rate being zero for those labeled with a d. From the timelines, a sequence of states can be defined as "I," "R_w," "R_d," and so on, but only the w or d can be definitely assigned, and therefore these states are not directly or completely observed and must be inferred from the breakpoints.

The HSMM is suitable for modeling breakpoint data because its unobserved (hidden) states form a hierarchy for rainfall activity evolving over time. Within the hidden states, the breakpoint observations are modeled as bivariate (for the wet data) and univariate (for the dry data) mixtures of lognormal distributions, whereas the states follow a semi-Markov model in which transition between states takes place with a probability that depends only on the initial and final states of the transition and persistence within a state is handled through a dwell time distribution that specifies the probabilities that a state will persist for n ($n = 1, 2, 3, \ldots$) breakpoints. The distribution used was a modified geometric one in which the probability of $n = 1$ was free and remaining probabilities were geometric. HSMMs and hidden Markov models (HMMs, in which self-transitions are allowed) have been widely used, in meteorological contexts and elsewhere (e.g., Zucchini and Guttorp 1991; Sansom 1998, 1999; Bates et al. 1998; Hughes et al. 1999; Rabiner 1989: Elliot et al. 1995; MacDonald and Zucchini 1997; Sansom and Thomson 2000, 2001). The remainder of this section provides an informal description of the HSMM using Figs. 4 and 5 to illustrate, respectively, how well the model fits to the data and how it reveals the frequency with which changes from one state to another take place. A more formal description of the HSMM is provided in section 3b of Sansom and Thomson (2007).

There are two distinct types of breakpoints—the drys and wets, and the distributions of these for Invercargill are shown by the histogram in the upper panel of Fig. 4 for the drys and by the contoured scatterplot below for the wets. Because their rain rate is always zero, the only measure associated with dry periods is their duration in minutes. The 7082 dry durations have been logarithmically transformed for the histogram, in which it can be seen that they range in length from just a few minutes to a week or more and have a mode of approximately 30 min. With wets, for every duration, again in minutes, there is an associated rate in millimeters per hour that is the steady rate that persisted throughout the duration. Both durations and rates have been logarithmically transformed for the scatterplot in which the central (densely populated) part has been indicated by contours. Thus, the most frequent wets are those with durations of about 6 min during which rain fell steadily

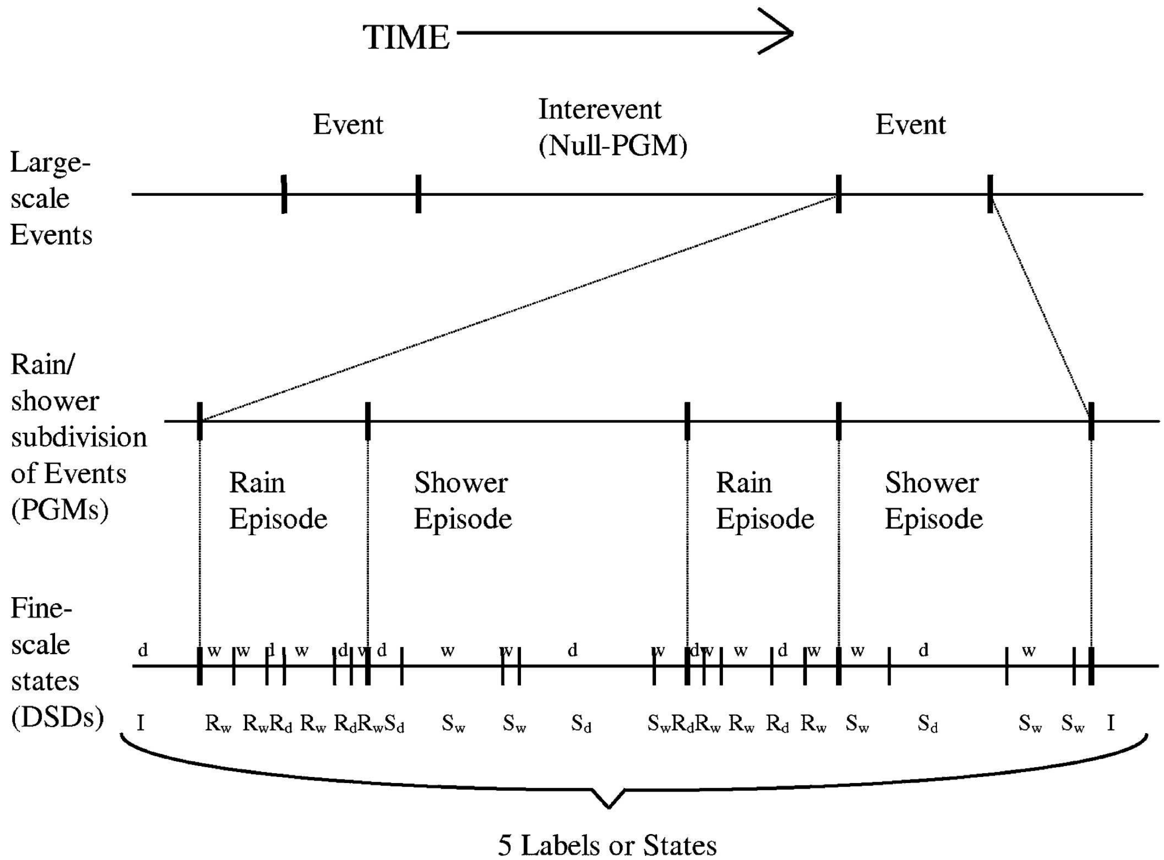

FIG. 3. Hierarchical division of time into large-scale precipitation events and dry interevents at the top, then events into rain or shower episodes, and, last, the episodes into individual wet and dry breakpoint durations. The d and w indicate dry and wet, which are known from the breakpoint data, whereas the R, S, and I indicate rain or shower episodes and dry interevents, which are not known from the breakpoint data.

at about 1.5 mm h^{-1}, but they range from under 1 min, with rates up to and occasionally over 100 mm h^{-1}, to perhaps 2 h, with low rates down to 0.1 mm h^{-1}. The breakpoints from Auckland and Wellington have distributions similar to those in Fig. 4.

In the HSMM, these distributions are assumed to be a mixture of normal components, each of which is associated with a "state" of the system. The number of components that best suits the data with respect to statistical significance and physical interpretation was found to be three for the drys and four for the wets (Sansom and Thompson 2003). The fractional representations, locations, and scales (also correlations between the variates for the wets) found for the components were such that, when added together, distributions closely resembling those of Fig. 4 resulted. This part of the HSMM might be termed the "static" part because the time ordering of the breakpoints is not indicated.

The "dynamic" side of the model is apparent in information about which transitions actually occur, the frequency of transitions between the states, and the dwell times in the states. These aspects are illustrated in Fig. 5 in which the locations of the wet states in the log(rain rate)–log(duration) plane are shown by circles and the locations of the dry states are shown by black circles along a log(duration) axis drawn in an arbitrary position at the top of the log(rain rate)–log(duration) plane. The transitions that take place between the states are shown by lines between the circles, with arrows showing the direction of change; most transitions are two way. The heaviness of these connecting lines indicates the frequency of the transition, and so, as can be seen by the tabulation in Fig. 5, 89% of the data are covered by eight transitions (4 two ways). The numbers inside the location circles of the wet states are the mean dwell times (i.e., mean number of breakpoints) in the state before a transition to another state takes place; for the drys the dwell time is always unity and is not shown.

The states represented by the circles in Fig. 5 need physically meaningful names, or labels, to fulfill the scheme of Fig. 3. On the principle that rain-type pre-

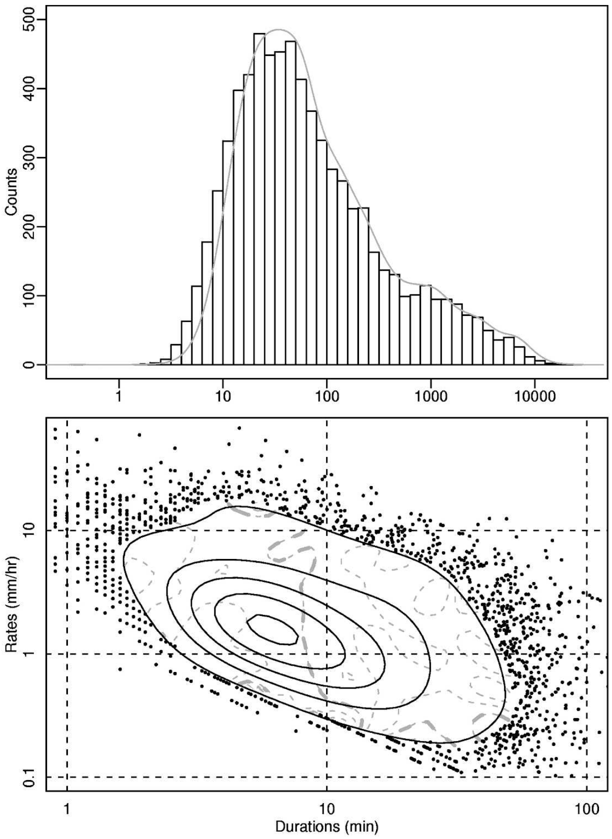

FIG. 4. The breakpoints of the analog period at Invercargill: (top) the drys as a histogram and (bottom) the wets as a contoured scatterplot, where only the outer points are plotted and contours indicate the frequency of points at and around the center of the scatter. The gray curves are for the Now data at Invercargill: the drys as an estimated density, and the wets as the percentage difference in frequency. The thicker dashed gray line indicates the 0% difference, and the thinner lines are at 50% intervals such that in the analog period the frequency of data with rates and durations close to its mode is higher than for Now.

cipitation is generally lighter but more persistent than shower-type precipitation, the states with mean dwell times of 4, 1.7, 1.9, and 1.3 (see Fig. 5) were labeled as *R*, *r*, *S*, and *s*, respectively, where the capitalization indicates the states with higher rain rates. For the dry states, the labels *r*, *s*, and *I* (for interevent) were used. In an actual series of breakpoints the following sequence might occur: after an *I* (mean for state about 350 min) of 500 min a wet *s* (state centered at about 6 min, 1.3 mm h^{-1}) occurs with a rate of 2 mm h^{-1} and lasts for 4 min, and then another wet *s* of 1 mm h^{-1} occurs and lasts for 3 min before a change to a dry *s* (i.e., a dwell time of two breakpoints occurred in state *s*, which has a mean dwell time of 1.3 breakpoints), and so on, with changes from dry *s* to wet *S* or *s* allowed but not to *R* or *r*.

5. Rainfall scenarios

Nearly 50 parameters are involved in the HSMM and each of the six datasets (i.e., Now and Future for three stations) have 10 000–20 000 points so that, with 200 or more points each, the parameters are well defined. However, the parameters are not readily understandable, and a direct comparison between those estimated from the Now dataset and those estimated from the Future dataset would be neither easy nor useful. Instead, the HSMMs can be used to simulate breakpoint datasets of arbitrary length that will have similar characteristics to the originating 5-yr period. These simulated datasets can then have annual statistics extracted from them and the comparison made, as in Fig. 2, through box plots of Total, Max, WetDays, and DrySpells for the actual data and that of the analog period.

In this way the information within the details of the breakpoints is exploited to provide well-defined estimates of long-term annual statistics from only 5 yr of data. These estimates are shown in Fig. 6, which is similar to Fig. 2 except the Now and Future were derived from 50-yr simulations of HSMMs (i.e., a period similar in length to those of the long-term datasets). The Long-Term box plots of Fig. 2 are repeated in Fig. 6, and a comparison of them with the Now box plots provides some validation of the model that was more fully explored by Sansom and Thompson (2003). They reported that in their spatial variation study over the 563 points of a 6-km grid covering the southern part of New Zealand's North Island the mean differences between HSMM estimates of Total, Max, and WetDays and independent assessments made directly from observations were, respectively, 2.5%, 10.2%, and 3.2% but that differences of about 20% did occur at some of the grid points. In Fig. 6 significant differences can be seen between the Long-Term and Now medians for both Max and DrySpells. These may represent either model biases, which appendix B demonstrates arise from a lack of seasonality in the HSMM, or, despite choosing a recent period to match the last 50 yr as closely as possible (as described in section 3), they may represent real differences with recent Maxes being less than normal and DrySpells being longer. Despite such differences the overall appearances within each panel of the box plots, including those for Future, are much the same except for DrySpells at Invercargill and, to a lesser extent, Auckland. This conclusion is underlined by the results of Kolmogorov–Smirnov tests between the Long-Term and Now datasets shown in Table 1. Only for WetDays and Invercargill's Total were the Long-Term and Now distributions not significantly different,

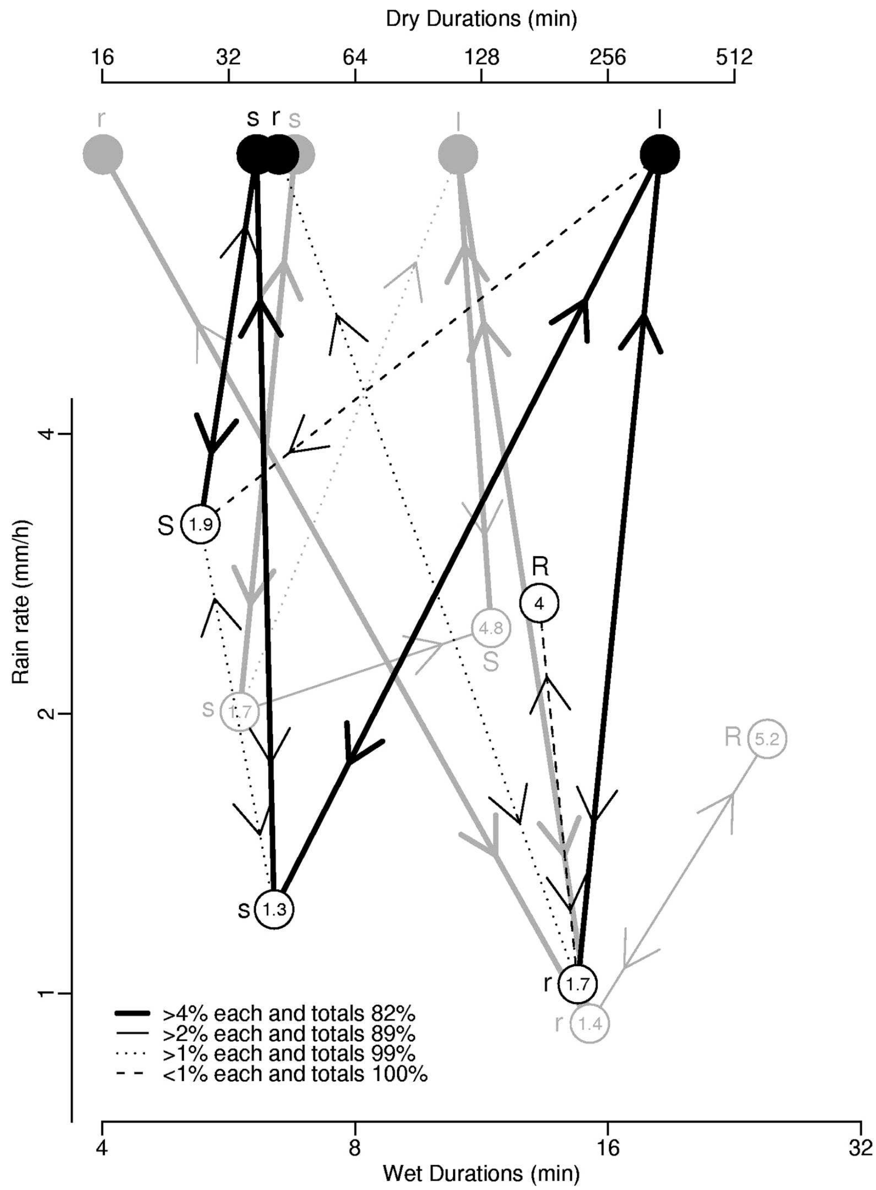

FIG. 5. The structure of the HSMM for the analog period at Invercargill in terms of which transitions between states are allowed and the relative frequencies of the transitions. The states are positioned either in the rate–duration plane for the wets or along a duration axis for the drys at their distribution's location parameter. The mean dwell (i.e., number of breakpoints during which no change of state takes place) in the wets states is shown by the number in the circles at the states' locations: a state change always follows a dry breakpoint. The gray pattern is for the Now data at Invercargill.

but when the bias was allowed for then, as shown in the rightmost column of Table 1, only DrySpells at Invercargill and Auckland remained significantly different.

Whether these are strictly model biases could only be resolved by fitting HSMMs to Long-Term, rather than Now, datasets, but such datasets do not exist and the resources for obtaining them from the pluviographs were unfortunately not available within the scope of this study. Despite these biases, any significant changes between the simulated Now and Future climates will be taken as significant trends because the biases will be assumed to be largely model based and so similar in both the Now and Future simulations. At all stations both Total and WetDays increase such that approximately, but less so at Auckland, what was the upper quartile becomes the lower quartile. Max decreases at

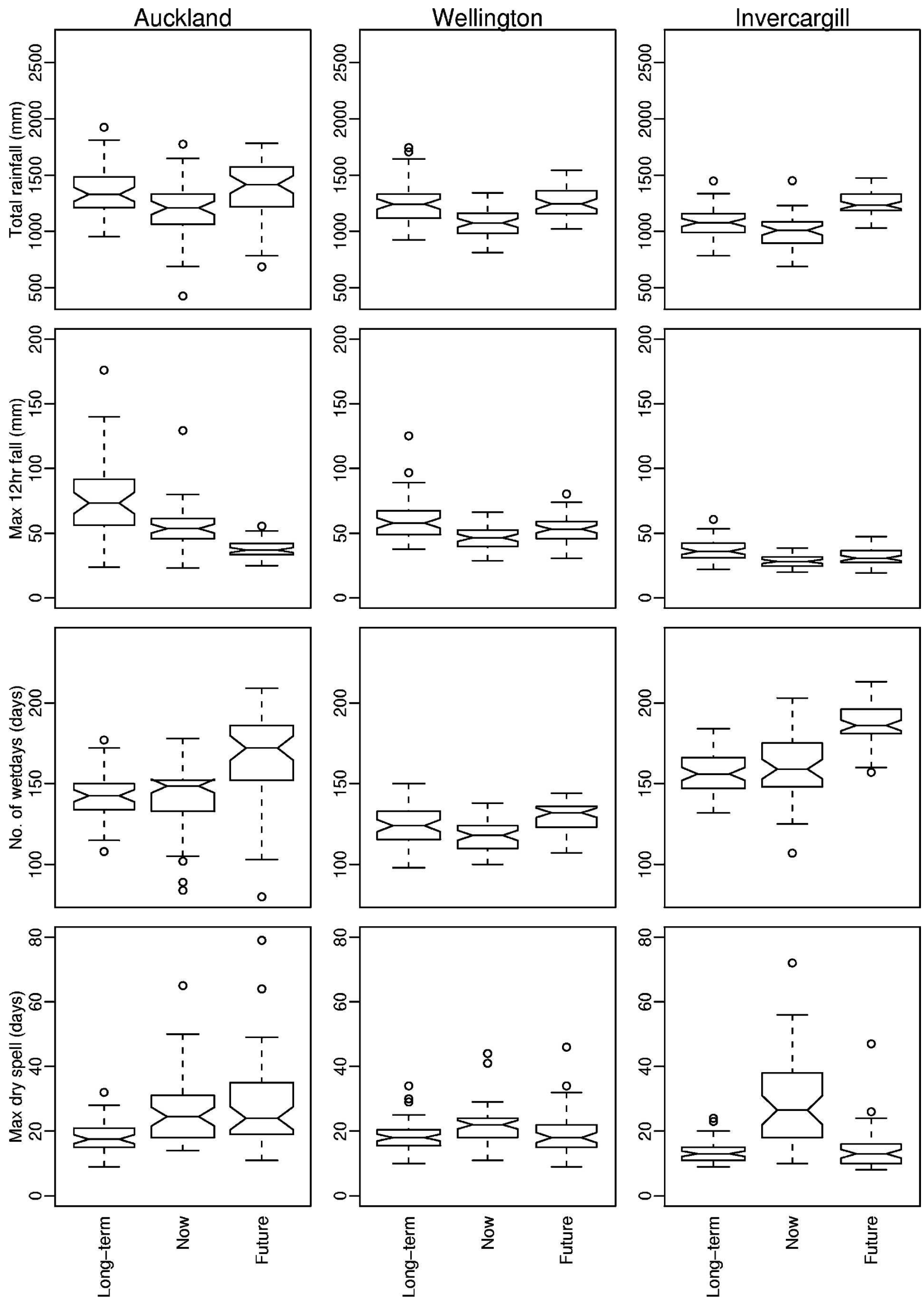

FIG. 6. Similar to Fig. 2, except that the Now and Future datasets are from 50-yr simulations of HSMMs fitted to the respective 5-yr periods.

TABLE 1. The p values of Kolmogorov–Smirnov tests between the Long-Term and Now datasets. The difference between the medians is taken as the bias, and p values for bias-corrected tests are also given.

Location	Statistic	p value	Bias	p value (bias corrected)
Auckland	Total	0.0178	119.6	0.9551
	Max	<0.0001	19.8	0.1540
	WetDays	0.3182	−6	0.3666
	DrySpells	0.0015	−7	0.0311
Wellington	Total	<0.0001	167.4	0.5287
	Max	0.0003	11.4	0.2955
	WetDays	0.0499	6	0.9488
	DrySpells	0.0039	−4	0.9909
Invercargill	Total	0.0775	69.1	0.8451
	Max	<0.0001	7.8	0.3520
	WetDays	0.4153	−3	0.8451
	DrySpells	<0.0001	−13.5	0.0005

Auckland and DrySpells decrease at Invercargill such that what was the lower quartile becomes the upper quartile; otherwise little change is seen for these extreme statistics. These changes result from what might be termed the "All Change" scenario, but other possible scenarios can be explored, as discussed below.

In Figs. 4 and 5 the Now data and model for Invercargill are shown in gray tones and the Future is shown in black. For the drys it can be seen that there are fewer short periods in Now and just a few more long periods. For the wets, the Now is shown as a percentage frequency difference from the Future, with the thicker dashed gray line being the zero percentage difference and the lighter gray ones being at 50% intervals. The sign of the difference is not shown, but those on the left are such that in Now there are significantly more short wet intervals and fewer long ones. Thus, the change in Future is that the number of long dry intervals decreases slightly but the number of short dry breaks increases; also, precipitation becomes more persistent, with more 10–60-min periods with moderate rates and fewer short periods with lighter rates. Auckland had similar changes, but at Wellington long dry periods became more frequent in Future and rainfall became less persistent.

The changes shown in Fig. 5 that take place in the model between the Now and Future datasets seem somewhat arbitrary with a split no longer required between the states with the higher rates and longer periods (i.e., those with mean dwells of 4.8 and 5.2); instead, the shorter wet durations split into components with light and moderate rates and mean dwells of 1.3 and 1.9, respectively. Various other changes can also be seen in the locations of the dry components and the strength of the transitions between all of the states. Without any physical guidance the model fitting will find the most probable, or statistically significant, fit, but this may not be the best physical model. However, two extreme physical conditions can be examined because it is possible either to retain the static structure of the Now fit when fitting to the Future or, as an alternative, to keep the dynamic structure. (It would be possible to keep parts of one structure with or without allowing changes in the other, but there is little guidance on what might be the most appropriate parameter values to retain.)

When the static structure is retained then the location and variability of the states are not changed, only the mean dwells (i.e., numbers in the circles of Fig. 5) and the strengths of the transitions. This result forces the PGMs to continue operating without change despite any climate change, and it is only the frequency and order in which they operate that changes. On the other hand, when the dynamic structure is retained then the location and variability of the states change so that the circles in Fig. 5 shift but the mean dwells and strength of the transitions do not change. This situation allows the operation of the PGMs to change but forces their frequencies of occurrence to remain as they were before any climate change. Thus, the effect of climate change on the frequencies of frontal systems and areas of convection rather than on their intensity was assessed through the "Keep Statics" scenario, whereas, the effect of their level of activity, while maintaining the general frequency of weather systems, was assessed through the "Keep Dynamics" scenario.

To introduce seasonality into the HSMM, a Keep-Statics route is statistically the most parsimonious (Sansom and Thomson 2007) with respect to extra model parameters, and it is physically most likely because PGMs cannot directly experience the time of year and a given set of "control inputs" should have the same effect whatever the season. On the other hand, with climate change the range of these control inputs will likely change and so will shift the activity level of the PGMs. Thus, Keep Dynamics might well be preferred over Keep Statics, but it is unlikely that either of these scenarios is absolutely correct. Examining both allows the exploration of what might be considered the extreme alternatives to the basic All-Change scenario that is founded entirely on statistical significance.

6. Discussion

Figure 7 shows box plots for statistics extracted from 1000-yr simulations of HSMMs fitted to Now and Future datasets for the three scenarios: 1) all HSMM parameters change, 2) just the dynamic ones change, or 3) just the static ones change. Use of the 1000-yr simula-

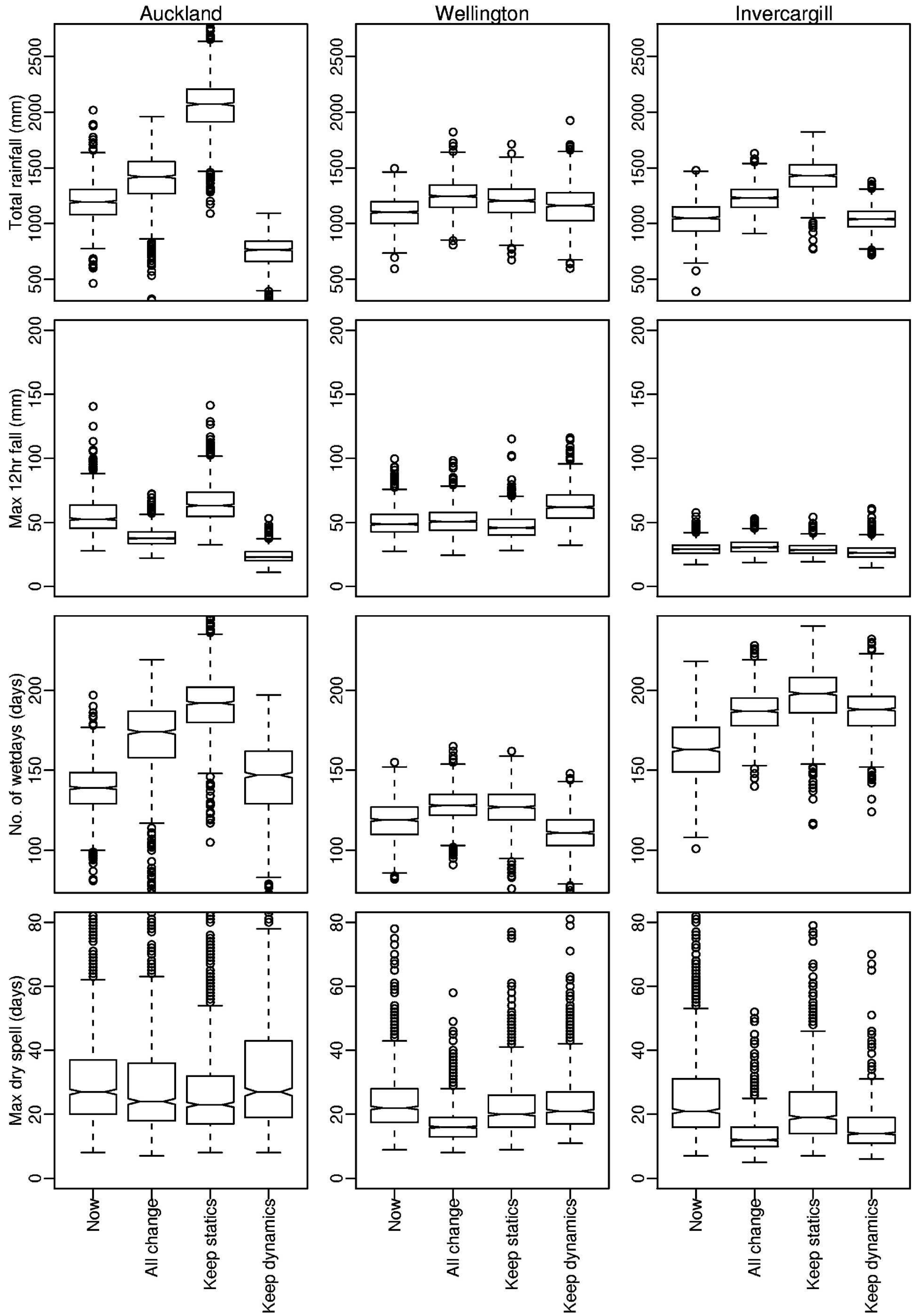

FIG. 7. Box plots for the annual statistics (Total, Max, WetDays, and DrySpells) at (left) Auckland, (middle) Wellington, and (right) Invercargill from 1000-yr simulations. In each panel, a box plot is given for conditions similar to the recent past and for the three climate change rainfall scenarios. (Note that a few of the simulation results that were outliers have been omitted.)

tions enabled precise location estimates to be made for the medians of the statistics, and changes in the rainfall climate will be discussed below in terms of differences between the medians. This suffices because, in general, the box sizes, whisker lengths, and character of outliers do not differ greatly within each panel so that the statistics' variability does not vary greatly between the simulations. To keep the same scales in equivalent rows of Figs. 2, 6, and 7 and maintain readability of the smaller boxes of Fig. 2, some of the outliers associated with the boxes of Fig. 7 have been omitted.

The top-left panel of Fig. 7 showing Total for Auckland clearly indicates that neither a pure Keep-Statics nor a Keep-Dynamics scenario is likely because, in the first case, Future with values near 1300 mm would be a run of five values below the 2d-percentile value and, in the second, a run of values well above the 99.9th percentile. The probability of either of these is very small. That these "Keep" scenarios gave such different results arose from how the model dealt with the imposed constraints of retaining either the static or dynamic structure. In the first case, the dynamic parameters must have been reestimated such that more time is spent (see the discussion below about Fig. 8) in the state(s) with the highest rain rates, giving a large increase in simulated Totals. In the second, the imposed dynamics have forced the static parameters of the wet states to be reestimated with lower mean rain rates, giving a large decrease in simulated Totals. Similar but less extensive differences between the Keep scenarios can be seen for other statistics and at other stations.

Thus, the value of the Keep scenarios is not in wholly adopting one, but in providing some insight into how the changes seen in the All-Change scenario have arisen and in qualitative guidance for what might be expected if climate change were expected to fall somewhere between All Change and either of the Keep scenarios. For example, there was a 19% increase in Total at Auckland that arose more from more frequent weather systems than from the systems being more intense, but if Future overrepresents changes in the frequencies of systems then this increase could be an overestimate. This qualification has little basis within this study, which assumes that Future is an unbiased sample of rainfall data that might be collected some time in the future. However, if it is conjectured, as in the previous section, that climate change is likely to change the level of activity of weather systems rather than just their frequency of occurrence then the qualification does apply.

Overall, Fig. 7 shows that mean conditions became wetter at all stations, with Total increasing by 200 mm at Auckland and Invercargill and by 100 mm at Wellington; also, WetDays increased by 30 days at Auckland and Invercargill and by 10 days at Wellington. Furthermore, all of these increases seemed to arise more from more frequent weather systems than from the systems being more intense. However, for extreme conditions the changes were small, and when significant they decreased; that is, Max at Auckland decreased by 27% and DrySpells decreased by 5 days at Wellington and by 10 days at Invercargill. The decrease in DrySpells is consistent with a generally wetter climate, but the decrease of Max is not. Furthermore, this change and the decrease in DrySpells at Invercargill, which was double the decrease at Wellington, were the only significant changes that seemed to arise more from weather system intensity rather than from frequency. If for these two cases more weight is given to the Keep-Statics scenario, which was dominant in all other cases, then a small increase in Max at Auckland could be countenanced as could a smaller decrease for DrySpells at Invercargill.

The box plots of Fig. 7 illustrated what changes might be expected for various climate change scenarios in the rainfall climate as measured by annual statistics, but little was revealed of changes at shorter time scales. Some issues clarified by a closer interpretation of the HSMM were, Would more or less time be spent raining? Would rain become generally lighter but more persistent? Or, would showers be expected to become heavier? Such questions could be easily answered if each datum also included one of the labels that were defined in reference to Fig. 5 at the end of section 4. However, the "hidden" part of the HSMM is the lack, in the data, of these labels, and the techniques of discriminant analysis are available to allocate a label to each data point. After such allocation, the contribution of each state to the total dry or wet duration and, for the wets, to the total rainfall accumulation, could be determined. However, no error-free discrimination technique exists, and so the contributions would be estimates that can be more directly found by using the probabilities for each data point that it was derived from each state. These are conditional on the whole dataset and are calculated during the HSMM fitting procedure, and from them the expected durations and accumulations from each state can be estimated.

Figure 8 shows these expected durations and accumulations as fractions of the whole; for example, at Auckland most of the Now dry time, which covers 94% of the total time, can be attributed to the interevent drys (I); the fraction due to breaks during rain-type (r) PGMs is small, but 10% is associated with dry intervals between showers (s). Continuing the example, over

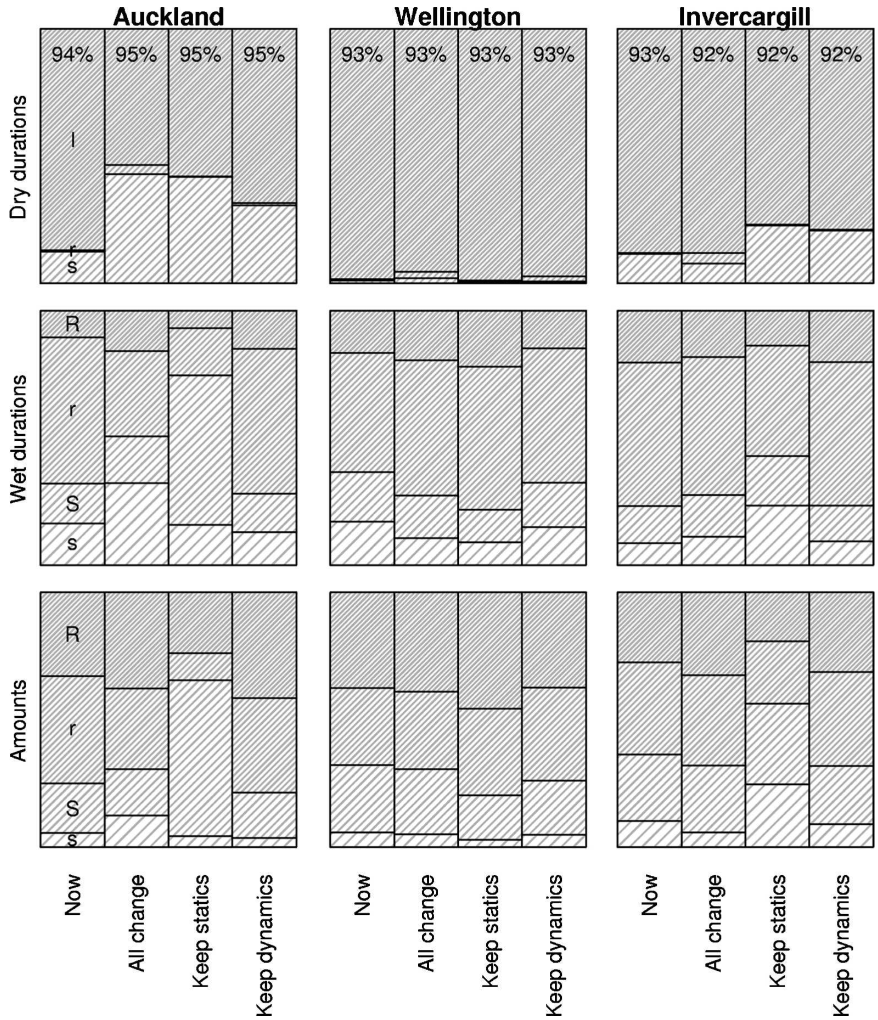

FIG. 8. The contributions from each state to the rainfall accumulation and the wet and dry durations at (left) Auckland, (middle) Wellington, and (right) Invercargill for conditions similar to the recent past and for the three climate change rainfall scenarios. The percentage given at the top of the dry duration bars specifies for the place and scenario the percentage of the time that it was not raining, and *I*, *r*, *s*, *R*, and *S* are explained in the text.

one-half of the wet time is spent during light rain (*r*) and the remainder is evenly divided between heavy rain (*R*) and showers (*S*, *s*). For amounts, nearly 80% result from rain (*R*, *r*), with more from light rain than from heavy rain, and the rest is mainly due to heavy showers (*S*), with only a few percent from light showers (*s*). The differences between Now and the various scenarios can be seen in terms of the fractional changes in the bar plots within each panel of Fig. 8. For example—and to complete discussion above regarding Total for Auckland—the contribution from heavy showers to both the durations and amounts increased by a large amount in the Keep-Statics scenario.

Despite this example, most other changes were small, especially in the All-Change scenario in which the largest differences to Now were the increase in heavy rain and light shower durations and amounts at Auckland. The other change that is shown in Fig. 8 is the change in the total amount of dry time: an increase of 0.55% at Auckland and decreases of 0.05% and 0.75% at Wellington and Invercargill, respectively. These changes and those shown in Fig. 7 imply that at Auckland, with less wet time despite more wet days, precipitation should become generally heavier because more total rain is expected, which lends weight to the suggestion above that a small increase in Max could be countenanced; there will be little change at Wellington; and, with both Total and wet time increasing at Invercargill, precipitation intensity should not change significantly there.

7. Summary and conclusions

The HSMM was able to capture the small-scale temporal structure of the rainfall process sufficiently well to provide realistic simulations from which annual statistics were extracted. Because it is not a seasonal model, most of the simulated statistics had biases, but their distributions were of the same character as that of the observed statistics. Thus, differences between statistics from simulations using HSMMs based on recent data and those based on data constructed from selected months in the past and used as a surrogate for the future were valid. The HSMM also allowed an assessment to be made about what was essentially different between the recent and surrogate future datasets and, as a consequence, how the actual future might qualitatively differ from the results obtained under different scenarios.

The HSMM analysis of the surrogate future data, which was assumed to be an unbiased sample of future rainfall, suggested that changes arise more from an increase in the frequency of weather systems than from a change in their level of activity. For the three New Zealand locations chosen, such a result is not unexpected. Most rain-bearing weather systems affecting New Zealand are transient disturbances in the midlatitude westerlies. Future scenarios based upon a stronger westerly circulation would imply more rapid movement of such disturbances and hence more frequent rainfall events. Although increased temperatures may in future be associated with increased rainfall intensity, GCM simulations are equivocal (Cubasch et al. 2001; Mullan et al. 2001; Whetton et al. 1996).

The increase in the frequency of precipitating weather systems resulted in a generally wetter climate, especially at Auckland and Invercargill, which are both more exposed to westerly airstreams than is Wellington. The largest changes were in the mean conditions, with increases of 10%–20% in both annual totals and the annual number of 1-mm wet days. At Invercargill there was an increase of 65 h in wet time (i.e., the total time in a year during which rain fell); thus, the overall mean rain rate was probably static, but at Wellington, where wet time was static, and especially at Auckland, where wet time decreased by 44 h, an increase in the mean rain rate was implied. After moderating the maximum 12-h rainfall at Auckland and maximum dry spell at Invercargill to be, like all other results, more influenced by the frequency of weather systems than by their intensity, the changes in extreme conditions are in accord with a wetter climate but change little. Maximum dry spells only shorten by a few days and maximum 12-h rainfalls only increase by 3–4 mm, even after allowing for the HSMM's bias toward simulating lower-than-observed values. For New Zealand, climate records (Penney 2001) show that the average annual 12-h maximum is approximately 3% of the average annual total; thus, with it increasing on average by 100–200 mm, the 12-h-maximum on-average expected increase is 3–6 mm. There appears to be no suggestion that extreme conditions will change out of proportion to the changes in mean conditions.

GCM simulations of future climate for the coming few decades in midlatitude locations (e.g., Kharin and Zwiers 2000) show only small mean precipitation changes, but increased extreme rainfalls and reductions in average return intervals for heavy rainfalls are common. The results presented here suggest that changes in extreme rainfall amounts in midlatitudes may, at least over the medium term, not be as marked as suggested by GCM simulations. However, these results have, of necessity, been based on the single sample of surrogate data that was available and so depend on this sample being representative of the future rainfall climate.

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APPENDIX A

Monthly Correlations

Figure A1 shows the month-to-month correlations of the rainfall accumulations in all of the datasets used in this paper. All of the 95% confidence intervals overlap, and most of them include zero within the confidence interval. However, with one exception, the tendency is for the correlation from one month to the next to be small and positive. The exception was for an actual period of continuous data while all three analog datasets had correlations that were similar to those of the Long-Term datasets. Thus, despite consecutive months within the analog sets never being actual consecutive months, the appropriate small positive correlation occurred, and, as mentioned in the text, it can largely be attributed to the seasonality of rainfall.

APPENDIX B

Seasonality and Model Biases

The HSMM captured the rainfall climate, but biases occur in the rainfall statistics extracted from synthetic

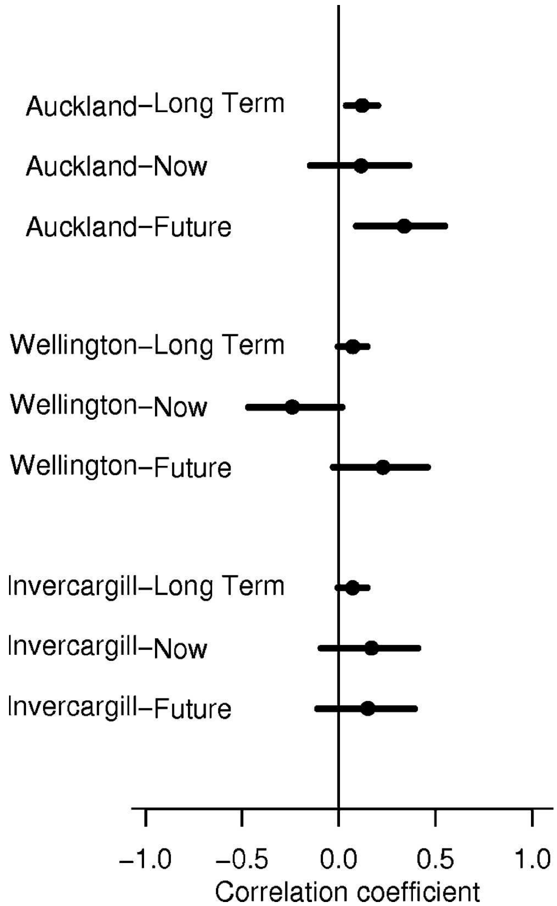

FIG. A1. The month-to-month correlations in rainfall accumulation for each of the datasets used. The 95% confidence interval is shown as a horizontal line.

data generated from the HSMM. This bias arises because it is not a seasonal model since the time of year of the breakpoints was ignored in the fitting procedures, and as a consequence no time of year can be attributed to simulated data points. However, a clear seasonal pattern does exist for rainfall with, for example, winters being wetter for Auckland and Wellington and autumns being wetter for Invercargill [for more details see Sansom and Thomson (2007)]. Thus, because the HSMM is not constrained to follow a seasonal pattern, simulations do not contain the persistence that may exist for seasonal time scales. For example, the concentration of heavy rain may be curtailed at times when it should be more persistent and so may bias Maxes in the simulations to smaller values than actually occur. In a similar way, without such "wet seasons" a dry period may become extended beyond what could naturally occur and this could also contribute to the smaller tendency for Total to be underestimated, as seen in Fig. 6.

Including seasonality in the HSMM is a nontrivial task requiring, as a first step, a physical investigation to determine where seasonality is expressed within the rainfall process so that the model can be enhanced in a physically meaningful way. Then, as a second step, the development, implementation, and verification of the algorithms for fitting the seasonal HSMM is required. The first step is described in Sansom and Thomson (2007), and work is under way on the second. The analysis below demonstrates that a fully seasonalized model would not have the model biases of the current HSMM by estimating from the historical record the annual rainfall statistics expected if there were no seasonality in rainfall. Thus, rather than introducing seasonality into the HSMM, the historical record was deseasonalized.

Apart from the three locations used in this paper, HSMM fits were available for another 86 stations within New Zealand for a period close to the Now period. At these stations, daily rainfall observations were also available, often for periods longer than that for which breakpoints were available, but only 52 stations had records with at least 30 complete years of daily observations. However, this is both a long enough record to establish at each station the biases that the HSMM produces in synthetic annual statistics and enough stations to determine the average of the biases. For each station/statistic combination the bias was calculated as the difference between the median of the actual record and the median of 30 yr of synthetic statistics scaled by the variability at the station. This variability was estimated by the mean of the pooled absolute deviations, where "pooled" indicates that the deviations of both the actual and synthetic statistics were included and "deviation" is just the difference between the actual value and the appropriate median. The left-hand panels of Fig. B1 show histograms of the biases and indicate that over the 52 stations the HSMM generally yields a drier climate because the actual Total, Max,[B1] and WetDays are greater than the synthetic values and the DrySpells are shorter.

Deseasonalized statistics were estimated from the historical records by finding at each station and for each statistic the month that is most similar to the year as a whole, because that is what the HSMM synthesizes. Thus, for each station the months that most closely average one-twelfth of the mean annual Total and WetDays were identified, and those months that most frequently yield the Max and DrySpells were also iden-

[B1] Only daily data were available for this analysis, and so Max refers to a maximum 1-day fall rather than a 12-h fall as in the rest of the paper.

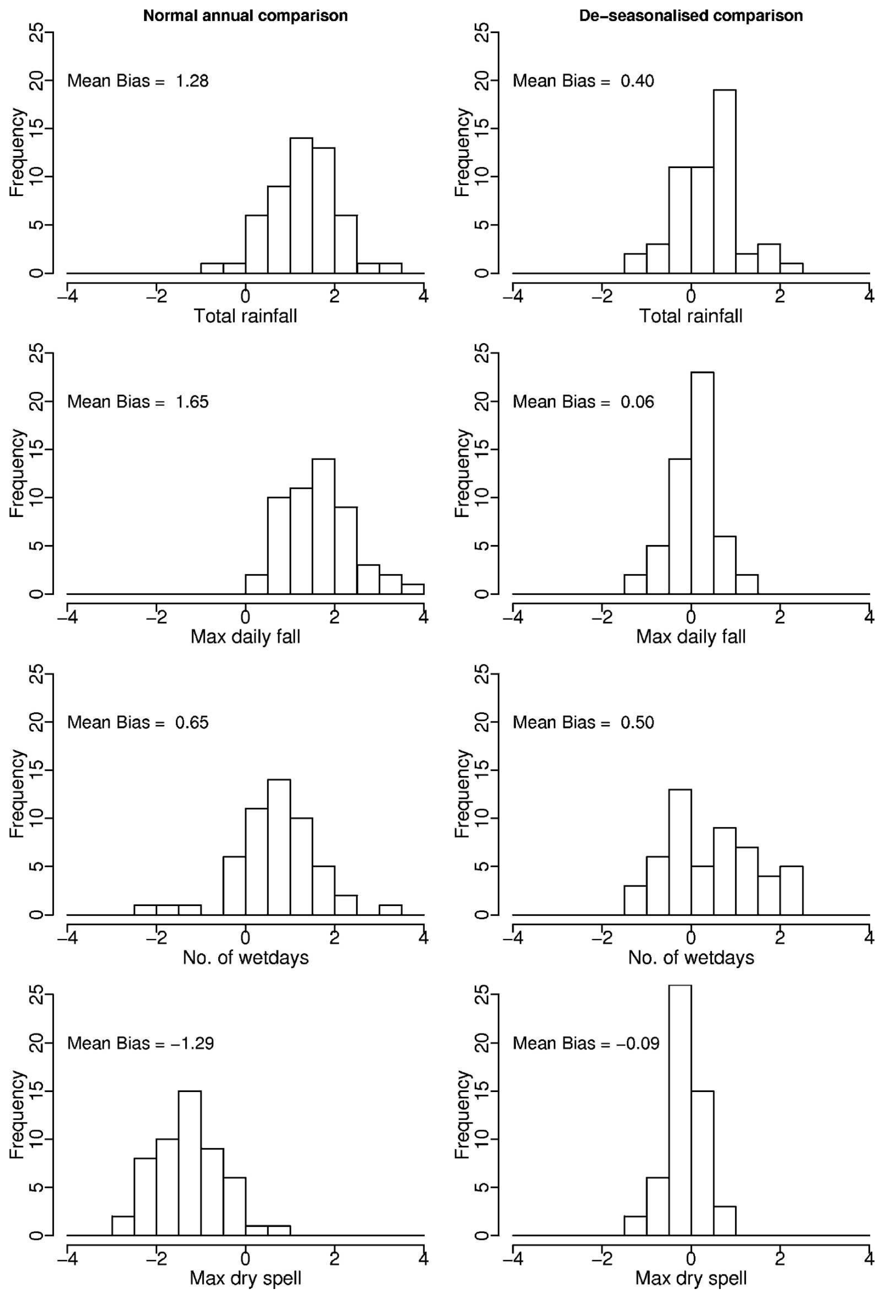

FIG. B1. Histograms from 52 stations for the four annual statistics for the biases of the synthetic statistics (left) when compared with actual values and (right) when compared with deseasonalized actual values.

tified. The biases were then recalculated by using those typical months rather than the full years with the Total and WetDays actual values multiplied by 12, and each synthetic year for Max and DrySpells was reduced to 30 days to be equivalent to that of the deseasonalized Max and DrySpells. The right-hand panel of Fig. B1 shows histograms of the recalculated biases and indicates that over the 52 stations the biases were centered on 0 with small mean values. This was particularly the case for Total, Max and DrySpells and was less so for WetDays, which had the smallest bias in the initial comparison. Also, the range of the biases for all of the statistics was smaller in the deseasonalized comparison.

Because, for the variability measure used, values between −2 and +2 can be considered as nonsignificant, even though biases do exist at individual stations, they are not significantly different from 0 and the overall mean biases are close to 0. Thus, the model biases can be attributed to the nonseasonality of the HSMM.

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