Impact of the El Niño–Southern Oscillation, Indian Ocean Dipole, and Southern Annular Mode on Daily to Subdaily Rainfall Characteristics in East Australia

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ABSTRACT

The relationship between seasonal aggregate rainfall and large-scale climate modes, particularly the El Niño–Southern Oscillation (ENSO), has been the subject of a significant and ongoing research effort. However, relatively little is known about how the character of individual rainfall events varies as a function of each of these climate modes. This study investigates the change in rainfall occurrence, intensity, and storm interevent time at both daily and subdaily time scales in east Australia, as a function of indices for ENSO, the Indian Ocean dipole (IOD), and the southern annular mode (SAM), with a focus on the cool season months. Long-record datasets have been used to sample a large variety of climate events for better statistical significance. Results using both the daily and subdaily rainfall datasets consistently show that it is the occurrence of rainfall events, rather than the average intensity of rainfall during the events, which is most strongly influenced by each of the climate modes. This is shown to be most likely associated with changes to the time between wet spells. Furthermore, it is found that despite the recent attention in the research literature on other climate modes, ENSO remains the leading driver of rainfall variability over east Australia, particularly farther inland during the winter and spring seasons. These results have important implications for how water resources are managed, as well as how the implications of large-scale climate modes are included in rainfall models to best capture interannual and longer-scale variability.

1. Introduction

Understanding rainfall variability at interannual and longer time scales is an important area of study with many practical implications for how we manage our water resources. This variability, which is often linked to both internally and externally forced fluctuations in the global sea surface temperature (SST) field (Bigg et al. 2003; Westra and Sharma, 2010), can often affect the weather patterns of entire continents via a set of large-scale pressure and circulation anomalies known as teleconnections that transmit these anomalies across large distances (e.g., Barnston and Livezey 1987).

In Australia, much of the early research into climate variability focused on the El Niño–Southern Oscillation (ENSO) phenomenon, which has been linked to precipitation anomalies across Australia, particularly over the eastern third of the continent (Pittock 1975; McBride and Nicholls 1983; Drosdowsky 1993; Chiew et al. 1998). This phenomenon is usually described in terms of coupled oceanic and atmospheric variability centered on the central and eastern tropical Pacific Ocean, with the extreme phases of El Niño and La Niña typically resulting in below- and above-average rainfall throughout large portions of Australia. Importantly, ENSO cycles between its extreme phases with a period of between approximately 3 and 7 years (McBride and Nicholls 1983;...
Drosdowsky 1993), although the predictability of individual ENSO events generally does not extend much beyond 1 year (Barnston et al. 1999).

The vast majority of the research described above has focused either on aggregate rainfall at seasonal time scales (e.g., McBride and Nicholls 1983; Drosdowsky 1993; Ropelewski and Halpert 1987; Chiew et al. 1998; Risbey et al. 2009a), or on extremes (e.g., Cayan et al. 1999; Gershunov and Barnett 1998; Liebmann et al. 2001, Pui et al. 2011). However, use of aggregated rainfall data can result in significant loss of information about the individual processes that make up interannual variability. For example, is an increase in spring average rainfall during La Niña events due to an increase in the number of discrete precipitation events occurring, or is it due to more intense rainfall occurring during each precipitation event? Such information is not only useful for developing a better mechanistic understanding on the nature of interannual variability, but also has significant practical implications in areas such as agriculture (e.g., the number of wet days per crop growing season, as well as the time between consecutive wet days) and flood estimation.

ENSO attribution on daily time scales has already been the subject of several studies, which capture various facets of the multiscale rainfall variability issue. For example, Ropelewski and Bell (2008) focused on shifts in fine temporal-scale rainfall statistics conditional to ENSO in the South American continent, whereas Samuel and Sivapalan (2008) analyzed the variability of inter- and intra-storm properties at three locations in Australia (Perth, Newcastle, and Darwin), which experience different climatic regimes. Finally, Nicholls and Kariko (1993) investigated only daily rainfall characteristics such as intensities and number of wet days, at five locations in east Australia that were influenced by the Southern Oscillation.

In this present study, we will build upon this earlier research, and address the following questions: 1) to what extent are rainfall occurrences and the intensity of rainfall per occurrence affected by these climate modes? 2) Are these changes also reflected when considering individual storm events using the subdaily rain gauge dataset? 3) Do these changes fully account for observed variability at the seasonal and longer time scale? To this end we will use a much larger dataset of both daily and subdaily precipitation sequences across east Australia. This region is selected because of the abundance of data compared with other locations within Australia, together with the strong association between rainfall and climate modes as documented in earlier studies (e.g., Nicholls 1997; Chiew et al. 1998).

While ENSO is recognized as the leading source of climate variability in Australia, other climate modes are known to have significant impact on regional rainfall (e.g., Risbey et al. 2009a; Hill et al. 2009). The influence of various climate modes increases the complexity in the attribution and thus prediction of seasonal rainfall, which is further exacerbated by complexities within ENSO itself (e.g., Westra and Sharma 2006). Thus, a second goal of this present study is to evaluate the impact of other major climate modes on daily and subdaily rainfall statistics. To this extent, we focus on the Indian Ocean dipole (IOD), which is of tropical origin, and the southern annular mode (SAM), of extratropical origin, both of which have significant impact over regional east Australia during austral winter and spring (see, e.g., Risbey et al. 2009a). The study presented here therefore adds to the body of research in this area by extending the analysis to the finest subdaily time scales, encompassing ENSO and these large-scale climate modes, using the long record of daily and subdaily rainfall datasets as the basis for the analysis.

The remainder of the paper is structured as follows. In section 2, the data and methodology used to conduct our analyses in this study are described. Section 3 is reserved for presenting results on the impact of ENSO on daily and subdaily rainfall statistics. The effects of the IOD and the SAM, and their potential influence on the ENSO–rainfall teleconnection, are explored in section 4, and conclusions are presented in section 5.

2. Data and methodology

a. Rainfall data

Rainfall data for this study comprises daily rainfall and subdaily (hourly) rainfall records. The daily rainfall data is based on a set of high-quality rain gauges throughout Australia that were identified by Lavery et al. (1997). For the purpose of this study, only locations with near-complete records (defined as less than 1% of days containing missing data) over the period from 1920 and 1999 were used. A total of 88 high-quality continuous daily rainfall records across Australia met this criterion, and that the locations of the rainfall stations provide reasonable spatial coverage for east Australia. For subdaily rainfall data, a total of 34 rainfall stations maintained by the Australian Bureau of Meteorology were used. The number of the stations used is less than that for the daily rainfall because of missing data at a number of stations. Our constraint in this case was to retain the longest possible records while ensuring less than 15% of the data was missing, with seasons where data was missing not considered in the analysis. As a result, these available stations are sparsely distributed and concentrated over the southeastern region. These stations have an average record length spanning 54 yr...
from 1952 to 2005, with each record containing at least 40 yr of data.

b. Climate indices

To examine the effect of the climate modes on the daily and subdaily rainfall variables, we used a single index representative of the evolution of each mode. The Southern Oscillation index (SOI), defined as the anomalous pressure difference between Tahiti and Darwin, is used as an indicator for ENSO activity. As demonstrated by Risbey et al. (2009a), rainfall correlations across Australia are not sensitive to whether SST-based indices or SOI are used to represent ENSO variability. This is because the SOI is highly correlated to the SST-based indices (Barnston et al. 1997). Indeed, our results remain largely unaltered when the Niño-3.4 index was used. The dipole mode index (DMI; Saji et al. 1999), which is defined as the difference in SST anomaly between the western and eastern tropical Indian Ocean regions, is used to represent the evolution of the IOD (Rayner et al. 2003). The index of Fogt et al. (2009) based on the difference between normalized monthly zonal mean sea level pressure at 40° and 65°S is used to describe the evolution of the SAM.

c. Multiscale rainfall variables

Rainfall variables derived from the daily and subdaily data were selected to explain variations occurring at seasonal time scales. An ENSO event typically initiates in late austral autumn, peaks in summer, and dissipates in the autumn of the following year. While the timing of ENSO impacts on rainfall may vary spatially even in east Australia, we have primarily focused on variables that were computed from the winter (June–August (JJA)) and spring (September–November (SON)) seasons as they coincide with the maximum impact period for the majority of stations in east Australia (Chiew et al. 1998). These seasons also coincide with the period of significant correlation between east Australian rainfall and the IOD, as well as the SAM (e.g., Risbey et al. 2009a; Hendon et al. 2007), and are thus relevant for assessing the interaction of impacts among the climate modes. Here, we derived three variables computed from the daily rainfall data for each season:

1) Rainfall total (from aggregated daily rainfall),
2) Number of wet days, and
3) Rainfall per wet day.

From the subdaily rainfall data, we derived the following variables:

4) Number of wet spells,
5) Average wet spell length, and
6) Rainfall intensity per wet spell. A wet day occurs when daily precipitation is equal to or exceeds 1 mm as defined by the Australian Bureau of Meteorology (BOM; available online at http://www.bom.gov.au/climate/change/about/extremes.shtml). It is noted that seasonal rainfall total is a function of both number of wet days and rainfall intensity of each wet day within the season. The wet days are in turn attributed by the characteristics of a “wet spell” within each day. A central assumption pertaining to the subdaily variables is the definition of a wet spell. Rainfall is often reported as falling in “events” or “storms” whose beginning and end are defined by rainless intervals (dry spells) of a fixed duration minimum interevent time (MIT), with a wide range of values previously adopted for the MIT from 15 min to 24 h (Dunkerley 2008). In line with Tsubo et al. (2005), a 3-h MIT was used here to distinguish between separate rain events or wet spells to allow for a compromise between the independence of rain events and intraevent variability in rain rates. We considered this MIT to be appropriate in this case since the focus of this study is not to obtain the most accurate storm separation threshold, but to perform a comparative analysis across a vast region with varying climatic regimes.

d. Impact of climate modes on rainfall variables

To evaluate the impact of the climate modes on the daily and subdaily rainfall variables, a linear regression analysis is implemented. The regressed rainfall variables onto the climate indices are expressed as percentage change from the corresponding mean values in response to one standard deviation of the climate index. The impact of interactions between the different climate modes on rainfall variables is evaluated using multiple linear regression. Furthermore, to isolate the influence of a certain climate mode, a partial regression analysis is used if two climate indices are found to be significantly correlated with each other for a particular season. This widely used technique (see, e.g., Risbey et al. 2009a; Cai et al. 2011) involves first removing the linear component of a given time series (e.g., SOI) from a time series of interest (e.g., DMI) and a rainfall variable before performing regression between the two. While many previous studies involved the use of standard correlation methods, we have elected to apply linear regression as it enables the ranking of each rainfall variable based on sensitivity to rainfall through magnitude of percentage change. This was used in preference to criteria based on statistical significance, because practically useful or important relationships may only be marginally statistically significant, for instance due to a limited sample size. Conversely, in the case of hydroclimatology research in particular, sensitivities or impacts arising from
statistically significant relationships can be very small such that they may be of limited practical value (see Clarke 2010). Nonetheless, statistical significance is still reported to provide an indication of a statistically significant relationship.

While the linear regression approach is useful, as previously adopted in various related studies (e.g., Nicholls and Kariko 1993; Chiew et al. 1998; Risbey et al. 2009a), it relies on the assumption of linearity in the relationships between variables. This assumption has been found to be reasonable for aggregate seasonal rainfall (e.g., Westra and Sharma 2010). Furthermore, since a comparison of correlations computed based on the Pearson product moment agrees well with the nonparametric rank-based correlation performed in this study, this suggests that our assumption of linearity is reasonable. As such, for succinctness, much of the discussions in the next sections will be based with reference to the La Niña condition, since the linearity ensures that changes as a function of El Niño or La Niña are symmetric.

To specifically examine the nonlinear nature of the ENSO-driven rainfall impact, a composite analysis was also conducted. Meyers et al. (2007) conducted a careful study in the classification of years of El Niño and La Niña using a lagged empirical orthogonal function analysis. These ENSO years as identified by Meyers et al. (2007) have been adopted as a basis for our composite analysis. Here, the nonparametric Mann Whitney U (MWU; Mann and Whitney 1947; Xu et al. 2003) and Kolmogorov–Smirnov (K–S) tests (Smirnov 1948) are used. In this case, we use a one-tailed MWU test to infer whether there is a significant shift in the probability distribution of each rainfall statistic in a particular direction, at the 95% significance level. The K–S test on the other hand uses the maximum absolute difference between the cumulative distribution curves from two samples to test if the samples come from different populations. Here, we use the K–S test to ascertain if rainfall variables from the El Niño and La Niña distributions are significantly different from each other at the 95% level. In addition to hypothesis tests, we also present density estimates of the rainfall variables such that notable differences, where present, can be identified via visual inspection. As our study essentially concerns interannual characteristics of daily/subdaily rainfall variables arising from the climate modes, linear trends, although generally small over the entire period of analysis, were removed from all variables prior to the above analysis to avoid introducing biases to the correlations between variables. The best-fit estimation of linear trends from all time series was done via the least squares method.

### 3. Daily and subdaily rainfall variability linked to ENSO

Results from linear regression of the SOI onto the daily rainfall variables show a significant increase in winter and spring rainfall totals at nearly all stations across east Australia as associated with a positive change in SOI (i.e., a La Niña condition; Figs. 1a,d). This finding is in agreement with previous studies (McBride and Nicholls 1983; Kane 1997). However, it is particularly interesting that these changes in rainfall totals, on the continent scale, are found here to arise more predominantly from changes in the number of wet days rather than rainfall intensity per wet day, as revealed in Figs. 1b,c,e,f. Furthermore, regression analysis for the subdaily variables reveals that changes in the number of wet spells are significant across many stations (Figs. 2a,d), compared to those for the duration and intensity of the wet spells that, on the other hand, show insignificant changes (Figs. 2b,c,e,f). This suggests that most of the changes to the rainfall totals appear to stem from changes in the number of occurring wet spells.

Note that the direction of changes at nearly all of the stations is uniform across most of the domain being analyzed, with the exception of the eastern coastal fringe where the changes are of a lower magnitude and generally not statistically significant, although they are of the same sign (Figs. 1 and 2). This was also found in earlier work by Timbal (2010), who used this to highlight the additional difficulty in characterizing variability across the east Australian coastline. Nevertheless, this region is only a small part of the study domain, and given the spatial homogeneity elsewhere, we present the region wide average percentage change for each rainfall statistic in Table 1 to aid with interpretation of the results. The corresponding proportion of number of stations that are statistically significant is also shown in Table 1 as an indication of field significance. For completeness, we also present the results for austral summer and autumn. With respect to daily rainfall variables, Table 1 shows a progressively stronger rainfall impact into the spring season, with a 17% increase in rainfall per positive standard deviation change in SOI. It also reveals that changes to the seasonal rainfall total are in general more apparently driven by changes to the number of wet days (11% increase) with a much higher proportion of stations returning statistical significance, as compared to the less pronounced changes and lower field significance in the rainfall per wet day statistic. Table 1 further shows that the only subdaily rainfall variable to exhibit any significant change is the number of wet spells across east Australia. It should be noted that changes to aggregated statistics such as total rainfall
amount, number of wet days, and rainfall per wet day derived using the subdaily rainfall data for the east Australian region were consistent with the same variables computed using daily rainfall. This represents a validation of the quality of the subdaily rainfall data, and suggests that the lower proportion of statistical significance may be explained simply by the shorter record lengths and increased missing data.

Based on these results, we suggest that the implications of ENSO on multiscale rainfall change averaged over the entire east Australian region are in general driven by changes in the number of wet spells occurring within a day, rather than their length or intensity. Thus, these changes in turn explain the changes in the number of wet days rather than rainfall per wet day. Regional variations exist whereby either or both the number of
wet days and intensity appear important at a few stations, possibly due to processes other than ENSO. Nonetheless, our results appear consistent with those of Nicholls and Kariko (1993) who found, using only five daily-rainfall stations, that the Southern Oscillation primarily influences the number of rain events, and to a lesser extent their intensity. Examination of the physical processes behind this differing impact on

the number and intensity of rain events is beyond the scope of our study. It is likely that, among other things, stochastic behavior of the air trajectory associated with rain-producing synoptic systems can play a role, by influencing available moisture relevant for rainfall formation (Brown et al. 2009).

For the remainder of this section, we further examine the ENSO-driven rainfall characteristics by focusing on

Figure 2. Changes for subdaily rainfall variables at individual stations across east Australia corresponding to a +1 standard deviation change in normalized seasonal SOI. Blue and red circles denote an increase and a decrease in daily rainfall, respectively; while filled circles denote the statistical significance at the 95% significance level.
the composite analysis for the spring season (SON), during which the ENSO impact is maximum (see Table 1). As such, any notable changes as discussed above should emerge clearly in probability density plots and pass the MWU and/or K–S statistical tests (see section 2). Probability density function (PDF) plots of mean-removed (centered) daily rainfall variables at each station conditional to El Niño and La Niña are presented in Fig. 3, with the corresponding bold curves indicating the east Australia–wide averaged response. It can be seen that the seasonal rainfall total during La Niña years is higher compared to El Niño years at most stations (Fig. 3a). These changes can be attributed more apparently to the number of wet days (Fig. 3b), as noted by the clearer separation between the two clusters of probability distributions for the El Niño and La Niña phases, compared to those for the rainfall per wet day statistic (Fig. 3c). As a validation statistic, we have introduced a new variable, the dry spell length defined as number of intervening dry days between distinct wet days. If there is an increase in the number of wet days for a fixed time frame (season), it should logically follow that there will be a corresponding decrease in the length of dry periods, unless these wet days are consecutive rather than interspersed. Figure 3d shows that while dry spell lengths are shorter during La Niña periods, the extent of the separation in the PDFs between the El Niño and La Niña phases is not as distinct as that of the number of wet days. This suggests that a fraction of the increase in the number of wet days at some stations during La Niña is associated with episodes of consecutive wet days (see also Fig. 5).

The contrasting probability distribution in the number of wet days is also seen at the subdaily time scale. As shown in Fig. 4, the subdaily PDF plots show the clearest separation in the PDFs of number of wet spells, with an increased and decreased number of wet spells during the La Niña and El Niño phases, respectively (Fig. 4a). A curious result is the PDFs of rainfall intensity per wet spell (Fig. 4c), which are not only statistically insignificant between the opposing ENSO phases, but are also more skewed toward its mean. This result is consistent with that of Samuel and Sivapalan (2008) who did not find sufficient evidence (by virtue of the Student’s t and MWU tests) to conclude that average storm intensities differed between El Niño and La Niña phases in both Newcastle and Darwin, both of which are in east Australia.

It is worth noting that the composite PDFs reveal La Niña phases as having fatter tails in both the total rainfall amount and number of wet day statistics than El Niño phases (Figs. 3a,b). This suggests a certain degree of nonlinearity in the ENSO response, and that rainfall extremes during La Niña are more intense and/or frequent. Nonetheless, it should be noted that the results from linear regression analysis are still in qualitative agreement with those of the PDF analysis.

To conclude this section, we provide a continent-wide perspective of the ENSO influence by presenting the spatial distribution of the MWU and K–S tests for the daily rainfall at each station. The MWU tests (at the 95% significance level) were set out with the null hypothesis that each rainfall variable for El Niño is not significantly different from La Niña phases. The corresponding alternative hypotheses are as follows:

1) Seasonal rainfall total during El Niño is significantly lower than during La Niña (one tailed).
2) Number of wet days during El Niño is significantly lower than during La Niña (one tailed).
3) Rainfall per wet day during El Niño is significantly different than during La Niña (two tailed).
4) Dry spell lengths during El Niño are significantly larger than during La Niña (one tailed).

The K–S tests were conducted on the same rainfall variables to ascertain if their respective distributions were significantly different at the 95% level. Figure 5 shows the daily rainfall stations returning a p value of less than 0.05 (i.e., significant; in red) for each rainfall variable for the MWU (top row) and K–S (bottom row) tests, as well as statistically insignificant stations (in black).

The MWU test results confirm that the seasonal rainfall amount at most stations is significantly different
between El Niño and La Niña phases, except at a few stations along the east coast where local processes including orographic effects are more likely to interfere with ENSO signals. The MWU test for the rest of the daily rainfall variables shows the number of wet days exhibiting widespread significance across the region, in contrast to the rainfall intensity and dry spell length, which exhibit apparent heterogeneity with a relatively large proportion of stations showing statistical insignificance. This again confirms the number of wet days as the determining factor behind seasonal rainfall response to ENSO variability across east Australia, consistent with what was revealed from the regression analysis (Figs. 1d–f).

The K–S tests show that there are significant shifts in the PDFs of the seasonal rainfall total between the opposing ENSO phases. These shifts are most pronounced in the inland east region, with most of the statistically insignificant stations located along the east coast. The implication of the significance of these tests for the inland region of east Australia is that seasonal rainfall response to ENSO does not only involve shifts in the mean, but also the characteristics of its probability distribution. However, note that the shifts in the PDFs of the underlying daily rainfall characteristics paint a more mixed picture than the shifts in the mean, suggesting that they cannot be solely attributed to number of wet days. Rainfall per wet day as

![Fig. 3. Probability density function plots of daily rainfall variables conditioned to El Niño (in red) and La Niña (in blue) years. Thin lines denote PDFs of mean removed variables for each daily rainfall station, while the thick lines represent east Australia region averaged values for all stations. Over the period 1920–99, there are 14 and 27 yr classified as El Niño and La Niña, respectively [see Meyers et al. (2007), their Table 2 for specification of the years]. Thin lines denote PDFs of variable anomalies for each daily rainfall station, while the thick lines represent east Australia region averaged values for all stations.](image-url)
well as the temporal distribution of the wet days can also play a role.

Similar tests performed on subdaily rainfall variables reveal that the changes to rainfall per wet day and the temporal distribution of wet days appear to be solely attributed to changes in the number of wet spells, with approximately 71% (24/34) of subdaily rainfall stations returning a significant result for the MWU test (spatial plots not shown here). In particular, this result lends further support to our argument that changes to rainfall per wet day is caused by changes to the number of within-day wet spells rather than changes to rainfall intensity.

We next turn our attention to the contribution by the IOD and the SAM, and how they may interplay with ENSO and/or exacerbate its impacts on east Australian rainfall documented thus far.

4. Contribution by the IOD and the SAM

a. IOD

The linear regression analysis on daily rainfall for the IOD presented in Fig. 6 shows a decrease in seasonal rainfall that is fairly uniform across east Australia associated with a positive one standard deviation DMI for the winter and spring seasons. These differences, particularly during spring, are driven more predominantly by changes to the number of wet days rather than rainfall per wet day (Fig. 6; see also Table 2). Previous studies have noted the notably significant correlation between the IOD and ENSO (e.g., Meyers et al. 2007; Risbey et al. 2009a). The linear correlations during JJA and SON between the SOI and DMI indices over the time period of our analysis (1920–99) are –0.45 and –0.60, respectively, both of which are statistically significant. The
higher correlation in spring is expected, as the IOD matures during this season before it dissipates in summer when ENSO peaks. Because of such substantial IOD–ENSO correlations, it is expected that the IOD impact on the daily rainfall statistics would be due partly to co-occurrences with ENSO.

The isolated effect of the IOD can be examined by removing the component from the DMI time series that is linearly correlated to ENSO, and then regressing it onto the time series of the rainfall variables in which the ENSO coherence has also been removed. Our results are presented in Table 2 and the figures that follow. From Table 2 and Fig. 7, a partial IOD (i.e., after removing the effect of ENSO from the IOD) has a much less significant impact on the daily rainfall variables during winter to spring. On the other hand, the partial regression on ENSO reveals that the impact of partial ENSO (after removing the effect of IOD from ENSO) appears to be less altered from that without the IOD removed, particularly in JJA since their correlations are weaker (Tables 1 and 2; Figs. 1 and 8). The effect of IOD on the ENSO impact is more notable in SON. Again, these effects generally arise from changes in the number of wet days rather than rainfall per wet day. These analyses suggest that ENSO appears to have stronger direct impact on rainfall over east Australia in winter than in spring by which time the interaction with IOD becomes important. This can be explained as follows. Direct impact of ENSO on northern Australian rainfall is via atmospheric pressure fluctuations as part of the Southern Oscillation. In addition, anomalous conditions in the Pacific associated with ENSO drive Rossby wave trains that propagate into the extratropics, influencing rainfall in the higher latitudes of east Australia (e.g., Hill et al. 2009; Cai et al. 2011). At the same time, ENSO tends to influence the evolution of the IOD and modulate convection in the eastern and western Indian Ocean that in turn drives poleward-propagating barotropic wave trains affecting rainfall across southern Australia (Cai et al. 2011). Cai et al. (2011) showed that
during winter the wave trains associated with the IOD emanate only from the eastern Indian Ocean, as ENSO tends to offset convection in the western counterpart during the developing IOD. In spring, however, both the western and eastern Indian Ocean convective regions, in association with stronger ENSO–IOD coherence, contribute to stronger rainfall effects over the southern parts of the continent (Cai et al. 2011), by conditioning cutoff low systems that are an important source of rainfall in the southeastern Australia (Risbey et al. 2009b). In addition, our results show that ENSO also impacts on rainfall intensity per wet day in the southern stations (Fig. 1f), and that this effect becomes apparent once the IOD effect is removed (Figs. 8d–f).

b. SAM

The SAM impact in winter shows notable spatial variations (Fig. 9a). Phases of positive SAM as associated
with a poleward shift of the subpolar westerlies, correspond to anomalously dry conditions in the southern parts of the region, including Tasmania. Rainfall increases are, however, seen in the eastern coastal regions, which become more widespread and apparent in SON, in association with anomalous easterly flows that intensify in this season (Hendon et al. 2007). As the SAM was not found to be significantly correlated with either IOD or ENSO during our period of analysis, partial regression analysis is not necessary and thus not performed here. Figure 9 shows that the maximum impact region and season for SAM is the east coast region in SON. This is consistent with findings in other studies that found the east coast of Australia experienced the largest increases during the positive SAM phase, which may be explained by anomalous easterly winds enhancing moisture advection from the ocean and hence increased orographic rainfall in this region (Sen Gupta and England 2007; Gillett et al. 2006; Hendon et al. 2007). Conversely, the positive SAM also resulted in rainfall reductions in the southern part of the region especially during the JJA period (Cai and Cowan 2006; Meneghini et al. 2007). Previous studies have attributed this decrease to the contraction of the westerly wind belt toward the poles (Hendon et al. 2007). However, despite the mixed response in total rainfall occasioned by SAM, it transmits its influence in a manner consistent with the other climate modes above: that changes, where present, are more pronounced in number of wet days compared to rainfall per wet day (Fig. 9).

It should be noted that the way in which the IOD and the SAM transmit their influence to subdaily rainfall variables mirrored that of ENSO, with changes, where present, almost exclusively limited to the occurrence of subdaily wet spells (results not presented here).

c. Interaction between IOD, SAM, and ENSO

For this section of analysis, we aim to test if interactions between the different climate modes resulted in enhanced effects on the three daily rainfall variables described above. A time series of yearly east Australia normalized rainfall, as well as the SOI, DMI, and the SAM index is presented in Fig. 10 as a visual aid. We first tested for changes corresponding to positive one and negative one standard deviation of SOI and DMI, respectively, using multiple linear regression (i.e., the combination that is expected to result in wetter conditions). We then paired positive one standard deviation of SOI and SAM index (again, based on the direction of change in index that produced coherent impact on rainfall variables) before including all three climate indices as predictors into the model. The results are summarized in Table 3, suggesting that the effect of stratifying rainfall variables to multiple predictors did not always translate to an additive effect to rainfall variables. In particular, the ENSO–IOD pairing resulted in minimal increase in magnitude of changes compared to ENSO alone. This result was not surprising considering that they are correlated. With respect to the SOI–SAM pairing, rainfall during spring season increased significantly, with up to 30% change in total seasonal rainfall amount that can be attributed to 18% increase in number of wet days, and 12% increase in rainfall per wet day (Table 3). Note that the effects of the SAM and ENSO are offsetting in the southern region during winter. However, when all three climate modes were included as predictors, no significant new information could be gleaned suggesting that interactions between these modes resulted in only minor changes to the dynamics of rainfall in east Australia.

5. Conclusions

In this study, we have explored daily to subdaily rainfall variability at several sites across east Australia. The main findings from our analyses can be summarized as follows:

1) Changes to seasonal rainfall amounts associated with ENSO variability over east Australia as a whole, particularly during the cool seasons, can be primarily attributed to changes in the number of wet days and
to a lesser extent, rainfall per wet day. Analysis of subdaily rainfall data has further established that changes to rainfall per wet day are in fact caused by changes to the number of wet spells per day, and not rainfall intensity per wet spell suggesting that it is the probability of rainfall occurrence, rather than the character of rainfall given that it has occurred, which is the dominant mechanism driving seasonal rainfall changes.

2) The impacts of ENSO and IOD in combination are fairly spatially homogenous on the continent scale. Spatial variations do nonetheless exist, with ENSO and IOD more strongly impacting the inland east and southeast regions, respectively. The SAM’s influence on rainfall is strongest over the east coast region during SON, but is associated with a more mixed rainfall response during JJA, with the southern part of the region experiencing opposite effects to the

FIG. 7. Changes for daily rainfall variables at individual stations across east Australia corresponding to a ± 1 standard deviation change in normalized seasonal DMI with the SOI signal removed. Blue and red circles denote an increase and a decrease in daily rainfall, respectively; while filled circles denote the statistical significance at the 95% significance level.
northern part. Despite having different maximum impact regions and seasons, the manner in which IOD and SAM impact on rainfall is somewhat similar to that of ENSO, in that changes to the number of wet days is overall more significant than rainfall per wet day.

3) ENSO has been found to be the primary driver of climate variability over east Australia during the long period of analysis (1920–99). While combination of the modes did occasionally produce additive effects such as the ENSO–SAM in SON, we found significant redundancy in the effects of climate modes in combination perhaps as a result of significant correlation with each other (such as the ENSO–IOD pairing).

Importantly, we have shown that insight into sub-daily rainfall characteristics may help explain changes
occurring at coarser time steps as well as assist with making some initial inferences into the physical mechanisms behind climate-mode-driven rainfall. Because rainfall intensity per wet spell remains fairly constant under the influence of climate modes, we suggest that the nature of the rainfall generating mechanism (i.e., stratiform vs convective) does not differ significantly as a result of climate mode influence. Rather, it is the frequency of rainfall events that are subject to change. It is interesting that teleconnections appear to influence the probability rather than the intensity of events when they occur. The processes by which each of the modes transmits their influence on rainfall characteristics warrant further investigation.

It should be noted that the influence of climate modes on rainfall characteristics over east Australia, and the relationships between the climate modes, can be modulated by lower-frequency modes such as the IPO (e.g.,

**Fig. 9.** Changes for daily rainfall variables at individual stations across east Australia corresponding to a +1 standard deviation change in normalized seasonal SAM. Blue and red circles denote an increase and a decrease in daily rainfall, respectively; while filled circles denote the statistical significance at the 95% significance level.
Cai et al. 2010; Kiem et al. 2003), as well as the warming trend. Such a modulation effect is not investigated in our study as the long record analyzed here captures both phases of the IPO, and as such biases due to the records representing a single phase alone are not expected. Our analysis is, however, useful for inferring a generalized role of the climate modes on rainfall characteristics. The effects of the IPO and long-term trends should nonetheless be investigated in future studies, in particular, concerning the possibility that the climate modes may influence finescale rainfall characteristics in a different way in a warming climate.

Finally, we wish to note a number of practical implications of the results presented here. The overriding importance of ENSO as the primary driver of rainfall variability in east Australia was emphasized, with percentage changes between around 16%–18% per standard deviation of the SOI during the winter and spring seasons, and slightly lower but also reasonably significant increases for the remaining seasons; this highlights that this mode of variability can have profound implications on flood risk and water resource availability. This is particularly the case in regions away from the eastern coastal fringe. The implications on flood risk are therefore less likely to be due to changes in the intensity of the flood-producing rainfall event during ENSO, with a related study recently also showing only a 3.2% and 4.6% change in the intensity of the annual maximum rainfall event pre standard deviation of the SOI for subdaily and daily rainfall, respectively (Westra and Sisson 2011). Rather, the increased number of wet spells during La Niña periods suggests that it is likely to be the catchment wetness (also referred to as the “antecedent moisture”) prior to the rainfall-producing flood event that is most likely to increase, highlighting that the joint probability of extreme rainfall and antecedent conditions need to be modeled in order to properly capture the implications of ENSO on flood risk (Kuczera et al. 2006). Analogous implications can be seen for other water resources applications, with infiltration properties and evaporation losses likely to be different for a larger number of less intense events compared with a smaller number of more intense events.

In conclusion, while the stochasticity of the climate system prevents exact sequence prediction of weather events within a particular season, we have shown that it is possible to obtain useful information on shifts in the important rainfall statistics using simple techniques, even if there is still variability that remains unexplained.


TABLE 3. Average percentage difference corresponding to the co-occurrence of different climate modes using multiple linear regression and proportion of stations that are statistically significant (in parentheses) for each rainfall variable of interest across 88 daily rainfall stations. Note use of $-1$ standard deviation DMI to highlight positive change in rainfall amount occasioned by $+1$ standard deviation SOI.

<table>
<thead>
<tr>
<th>Season</th>
<th>Variable</th>
<th>$+1$ SOI, $-1$ DMI</th>
<th>$+1$ SOI, $+1$ SAM</th>
<th>$+1$ SOI, $-1$ DMI, $+1$ SAM</th>
</tr>
</thead>
<tbody>
<tr>
<td>JJA</td>
<td>Rainfall tot</td>
<td>18.4 (0.74)</td>
<td>20.3 (0.86)</td>
<td>20.3 (0.80)</td>
</tr>
<tr>
<td></td>
<td>No. of wet days</td>
<td>11.2 (0.56)</td>
<td>13.0 (0.84)</td>
<td>10.0 (0.83)</td>
</tr>
<tr>
<td></td>
<td>Rainfall per wet day</td>
<td>8.4 (0.32)</td>
<td>7.5 (0.42)</td>
<td>6.4 (0.32)</td>
</tr>
<tr>
<td>SON</td>
<td>Rainfall tot</td>
<td>16.7 (0.72)</td>
<td>29.7 (0.93)</td>
<td>29.2 (0.92)</td>
</tr>
<tr>
<td></td>
<td>No. of wet days</td>
<td>10.9 (0.66)</td>
<td>18.4 (0.86)</td>
<td>17.7 (0.83)</td>
</tr>
<tr>
<td></td>
<td>Rainfall per wet day</td>
<td>6.0 (0.26)</td>
<td>11.8 (0.49)</td>
<td>10.5 (0.43)</td>
</tr>
</tbody>
</table>
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REFERENCES


