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Title:

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Date:

2017-01-01

Citation:

Earl, N. & Simmonds, I. (2017). Variability, trends, and drivers of regional fluctuations in Australian fire activity. *Journal of Geophysical Research*, 122 (14), pp.7445-7460. <https://doi.org/10.1002/2016JD026312>.

Persistent Link:

<https://hdl.handle.net/11343/293225>

Variability, trends and drivers of regional fluctuations in Australian fire activity

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Key points

Australian fire activity (2001-2015) is either decreasing or steady, with high temporal and spatial variability.

Decreasing fire regions are likely due to improved fire management, reducing the size and duration of bush fires.

Potential exists in Australia for skilful forecasts for future season fire activity based on precipitation and climate driver phase.

This is the author manuscript accepted for publication and has undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the [Version of Record](#). Please cite this article as doi: [10.1002/2016JD026312](https://doi.org/10.1002/2016JD026312)

Abstract

Throughout the world fire regimes are determined by climate, vegetation and anthropogenic factors, and they have great spatial and temporal variability. The availability of high-quality satellite data has revolutionised fire monitoring, allowing for a more consistent and comprehensive evaluation of temporal and spatial patterns. Here we utilise a satellite based ‘active fire’ (AF) product to statistically analyse 2001-2015 variability and trends in Australian fire activity and link this to precipitation and large-scale atmospheric structures (namely the El Niño–Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD)) known to have potential for predicting fire activity in different regions. It is found that Australian fire activity is decreasing (during summer (DJF)) or stable, with high temporal and spatial variability. Eastern New South Wales (NSW) has the strongest decreasing trend (to the 1% confidence level), especially during the winter (JJA) season. Other significantly decreasing areas are Victoria/NSW, Tasmania and South-east Queensland. These decreasing fire regions are relatively highly populated, so we suggest that the declining trends are due to improved fire management, reducing the size and duration of bush fires. Almost half of all Australian AFs occur during spring (SON). We show that there is considerable potential throughout Australia for a skilful forecast for future season fire activity based on current and previous precipitation activity, ENSO phase and to a lesser degree, the IOD phase. This is highly variable, depending on location, e.g. the IOD phase is for more indicative of fire activity in south-west Western Australia than for Queensland.

Index terms and keywords

3322 Land/atmosphere interactions

3309 Climatology

3305 Climate change and variability

3360 Remote sensing

3364 Synoptic-scale meteorology

Fire activity, satellite data, trends, climate driver indices, ENSO, Indian Ocean Dipole, Australia,

1. Introduction

Large-scale fires have an important influence on ecosystems over much of the planet and impact significantly on a wide range of human activities. Fires are caused both naturally (mostly by lightning) and anthropogenically (through carelessness or “prescribed” burning of forests and savannas for land clearing/management for agricultural and domestic uses). Fire affects all biomes to some extent, and *Mouillot and Field* [2005] estimate that 86% of global burned area (not including agricultural fires) during the 20th Century occurred in tropical savannas. Throughout the world, natural fire regimes are determined by climate and vegetation [*Marlon et al.*, 2008]. These, in turn, are related to precipitation and large-scale atmospheric structures and processes, such as the

Intertropical Convergence Zone (ITCZ), the subtropical ridges, the El Niño–Southern Oscillation [ENSO; *Nicholls*, 1991] and the Indian Ocean Dipole [IOD; *Cai et al.*, 2009]. Humans influence fire regimes both directly, through prescription burning and land-clearance etc. and indirectly, through changing land-use and anthropogenic climate change. Fire levels in many regions over the globe including Australia has been shown to follow a weekly cycle [*Earl et al.*, 2015], highlighting the immediate anthropogenic influence on their behaviour. In a changing climate and with population increasing, it is important to monitor fire levels to diagnose how they vary temporally and spatially and determine what drives these variations.

The availability of satellite data has revolutionised fire monitoring, allowing for a more consistent and comprehensive evaluation of temporal and spatial patterns of fire occurrence and area burned, especially since the launches of the MODerate resolution Imaging Spectroradiometer (MODIS) sensors on the Terra (launched December 1999) and Aqua (May 2002) satellites.

The nature of trends in Australian fire levels is somewhat ambiguous and there is considerable discrepancy between studies. *Giglio et al.* [2013] found a rapid decrease in Australian burned area (BA) from 1998-2011, especially between 2002-2010, followed by an upsurge in 2012. This is in agreement with the earlier analysis of *van der Werf et al.* [2010]. On the other hand, *Dutta et al.* [2016] found an increase in Australian 2007-2013 bush-fire frequencies (using a blend of NASA active fire (AF) and BA data to cross-validate and refine the majority of actual fire events used as ground truth information). To the knowledge of the authors, there has been no recent comprehensive study into regional Australian fire trends.

Better understanding of fire levels and climate variability can lead to improved ways to forecast the characteristics of an upcoming fire season [*Harris et al.*, 2008]. Short-term climate anomalies such as drought or periods of increased precipitation have a major influence on fuel loads particularly in grassland areas [*Harris et al.*, 2014]. Numerous studies that have found links between fire levels and climate variables such as temperature, rainfall and relative humidity in many regions of the globe, as well as Australia [e.g. *Spessa et al.*, 2005; *Felderhof and Gillieson*, 2006; *Harris et al.*,

2008, 2014]. In Australia climate variations are often linked to large-scale atmospheric circulation drivers such as ENSO and the IOD, known to affect vegetation, hence fuel loads, and the fire regime of the following months and seasons [e.g. *Verdon et al.*, 2004; *O'Donnell et al.*, 2011; *Harris et al.*, 2014]. These climate drivers induce significant anomalies of precipitation, relative humidity and cloud cover over Australia, which are fundamental factors for fire variability. Significant persistence is present in rainfall, on monthly, seasonal, and (to a limited extent) annual scales throughout Australia [*Simmonds and Hope*, 1997], also affecting the fire regime. The type of vegetation has also been found to play a significant role in BA in northern Australia (*Spessa et al.*, 2005).

El Niño (positive phase of ENSO) generally results in low precipitation for the Australian continent, and La Nina (negative ENSO) the opposite, often linked to potential fire conditions. There are many indices which provide a summary of ENSO conditions, and Niño3.4 (average sea surface temperature (SST) over 5°N to 5°S, 170°W to 120°W) can be regarded as one of the best [*Trenberth*, 1997; *Barnston et al.*, 1997]. ENSO is linked to the IOD, which has a more of an impact on western parts of Australia and again means drier (wetter) conditions when in positive (negative) phase. Fire weather-based indices are also useful for summarising the potential fire conditions, mainly for predictive purposes, representing the daily 'fire danger'. As an example the south-eastern parts of Australia use the McArthur Forest Fire Danger Index [see *Williams et al.*, 2001].

In this paper we address the following main research questions. (a) Are there significant trends in fire levels in Australia and how do these vary regionally? (b) What factors (including anthropogenic burning, current precipitation levels and antecedent precipitation) are most influential for explaining these variations? (c) To what extent can precipitation levels and climate indices (ENSO and IOD) be used to present seasonal outlooks for future fire levels in Australia? No study heretofore has used such a long time series satellite-based AF product at 0.1 degree resolution to analyse fire variability and trends with rigorous statistical significance testing.

2 Data and Methods

2.1 Fire Data

Fire levels (or their consequences) over a given region can be defined in a number of different ways and one must settle on a given metric before detailed analyses can be conducted. Measures that have been used in the literature include BA products, AF products, carbon monoxide emissions, economic losses, and number of human casualties caused by fires. Studies concerning fire variability and trends conducted with these different fire level measures can arrive at different conclusions [e.g., *Hantson et al.*, 2013, *San-Miguel-Ayanz et al.*, 2013, *North et al.*, 2015, *Doerr and Santín*, 2016].

BA and AF products are most commonly used to measure the fire levels of regions and both have advantages and disadvantages. BA products are less sensitive to changes in cloud cover and smoke since the algorithms used for BA draw upon multiple satellite overpasses and obtain cloud-free data collection after the fire event, whereas the AF daily product relies on passes from a single day [*Randerson et al.* 2012]. AF products however, have the ability to detect fires that are considerably smaller than the spatial resolution of an individual pixel due to nonlinearity dependence of radiative power on temperature [*Giglio et al.*, 2003]. This leads to greater accuracy in fire detection, though *Randerson et al.* [2012] have developed a method which uses to this dependence to develop a more accurate BA product. *San-Miguel-Ayanz et al.* [2013] show how AF and BA products can have opposite trends, e.g., over the European Mediterranean region for the period 1980–2010. Part of the reason for this difference is that most BA is due to a small number of large fires. For example, about 2% of their fires in the region account for over 80% of BA. Globally, the BA product suggests a smaller amount of area burned than the AF product in croplands and evergreen and deciduous needleleaf forests, greater amount for the non-forest classes and comparable totals for mixed and deciduous broadleaf forests [*Roy et al.*, 2008]. The reasons for these product differences are mainly associated with environmental spatial and temporal fire characteristics and remote sensing factors [*Roy et al.*, 2008].

While most analyses of large-scale fire in the literature have been undertaken with the BA measure, we conduct our investigation with the AF product. This is done for a number of reasons,

notwithstanding the drawbacks mentioned above. Firstly, AF products provide information on fire location and thermal IR radiance at the moment of the image acquisition by the satellite, and hence capture current fire levels including smaller prescribed burns for land management. By contrast the BA measure only quantifies an aspect of the *consequences* of fire levels [see also the comments of *Doerr and Santín, 2016*]. Another key reason we use the AF data in this analysis is that it is available at daily resolution. This means that we are able to establish whether weekly cycles are apparent in the data. Nothing in nature occurs with a precisely 7-day period and hence any such cycle which might appear in weather data [*Simmonds and Keay, 1997; Earl et al., 2016*] or fire activity [*Earl et al., 2015*] must be due to anthropogenic influences. This sort of information is valuable when interpreting fire trends, as we shall see later.

The MODIS Fire Team developed an AF product giving the location of burning fires. This daily (0000 UTC to 0000 UTC) global data (June 2000-present) is made up of two daily passes (from the TERRA satellite) at each location, and is downloadable from the NASA Earth Observations website (http://neo.sci.gsfc.nasa.gov/view.php?datasetId=MOD14A1_M_FIRE). Here, we use all available complete calendar years 2001-2015. The MODIS AF product builds on heritage algorithms for operational fire monitoring used with the Geostationary Operational Environmental Satellites (GOES) and Advanced Very High Resolution Radiometer (AVHRR) sensors, and provides information on the specific location of fires, leading to estimations of emitted energy and the flaming and smouldering ratio. For more information on the products and algorithms used, see *Justice et al.* [2006]. These data have been gridded at 0.1-degree resolution by the MODIS Land Science Team from the 1 km official MODIS AF product (MOD14A1). MOD14A1 is a level 3 tile-based product from MODIS Collection 5. Each pixel assigned to 'fire' has a count of the number of fires within the pixel, ranging from 0 to 100. The detections utilise infrared anomalies relative to the adjacent pixels during each of the satellite overpasses. The algorithm uses brightness temperatures derived from the MODIS middle infrared (4 μm) and thermal infrared (11 μm) channels, testing whether the signals in the identified fire pixels are different from those of surrounding, non-fire pixels [see *Giglio, 2015*].

Future updates of this dataset will be of even higher quality. Improvements have been made to the

fire detection algorithm and swath-level product, part of the Collection 6 land-product reprocessing (commenced in May 2015), which will reduce some of the limitations of Collection 5 such as fires obscured by smoke [Giglio *et al.*, 2016] and false alarms from solar reflection [see He and Li, 2011]. There are other AF products available, e. g. from GOES WF-ABBA [Koltunov *et al.*, 2012], Advanced Very High Resolution Radiometer based products [see Li *et al.*, 2001; He and Li, 2012], Suomi National Polar-Orbiting Partnership [Hillger *et al.*, 2013] and active fire products from the European Space Agency/ European Space Research Institute [Arino and Mellinotte, 1998]. However, MOD14A1 is ideal for our purpose given its global coverage, relatively long time series, data completeness and the fact that it is still operational.

2.2 Fire Counts

The annual and seasonal fire counts were calculated by summing each daily AF counts data for each 0.1 degree pixel within each study area, over 2001-2015. These data are in units of fire counts per 1000 km², gridded at 0.1° resolution by the MODIS Land Science Team. For numerical convenience we have normalised these data so that they represent the fire counts in each 0.1° x 0.1° grid box (adjusting for the fact that the area covered by a 0.1° x 0.1° grid box changes with latitude). Study areas were selected, and split up by state where appropriate, by region/geographical land-use (e.g. Queensland) or by clusters of fire-abundant areas (e.g. South-west WA).

2.3 Missing days

Of the 5478 days during 2001-2015, there were 208 (3.8%) with no data available. On all other days there were always missing data points due to the gaps between the polar orbiting satellite swaths, along with vast ocean areas not considered. The pre-processing analysis of these data for our analysis follows the procedure detailed in Earl *et al.* [2015]. The number of missing data points were totalled for each day and the mean number and standard deviation of these determined for each study area. If the number of 'no data' points were too high within each study region, these days were removed. The threshold for this was if that day had more than two standard deviations above the mean of missing data points. These missing days were replaced by the average of number of

fires for that year for that study area. This could lead to seasonal bias if the only available data for a region occurred at a time of high (or low) fire levels. The missing days for the Australian region ranges from 0 (in 2013) to 71 (in 2008) with these fairly evenly distributed throughout the seasons, so this bias is minimal.

2.4 Australian Rainfall, IOD and ENSO data and co-variance tests

Trend analysis was conducted using least squares linear regression analysis. Correlation analysis was performed, using the Spearman Rank based tests, between the standardised 2001-2015 seasonal fire count anomaly and to the standardised seasonal rainfall anomaly for each region in Australia. The standardised seasonal anomalies were calculated by taking the seasonal means for the number of fires (or precipitation totals) between 2001-2015, and calculating the seasonal deviation from the mean. These values were then divided by the associated seasonal means for standardisation. The non-parametric rank correlation test was used because the assumption of a normal distribution for the Pearson test is often not justified for the case for monthly rainfall (we comment that we correlated these data with the Pearson test and results were generally very similar to the Spearman).

The Australian Water Availability Project (AWAP) dataset was utilised in this study and is widely recognised as the most reliable rainfall dataset for the continent [Jones *et al.*, 2009; <http://www.bom.gov.au/jsp/awap/rain/index.jsp>]. As mentioned above, the 2001-2015 seasonal mean fire counts and mean seasonal total rainfall were taken and the deviation from this calculated for each season. This seasonal anomaly was then divided by the seasonal mean to provide standardised seasonal divergence for both rainfall and fire. These 59 2001-2015 complete seasonal anomalies (15 for March-May (MAM; Autumn)), 15 for June-August (JJA; Winter), 15 for September-November (SON; Spring) and 14 for December-February (DJF; Summer) seasons) were then detrended (linearly) before regression analyses were performed. This was done with all 59 concurrent seasons and with a fire lag of 1 to 7 seasons. This meant that for the full 2001-2015 to be utilised, the rain seasons (with a longer record) from 1999-2000 were also used. For example for a 3 fire season lag (from rainfall season), the 59 fire seasons from MAM 2001 to SON 2015 were correlated with the 59 rainfall seasons from JJA 2000 to DJF 2014/5. For the seasonal tests, we used

the same method, though compared each specific rain season (e.g. SON) with the corresponding 15 (or 14 DJFs) 2001-2015 fire seasons, using the same lag method. For example, if SON rainfall was compared to the following MAM fire, the 15 2000-2014 SON rainfall seasons would be correlated with the 15 2001-2015 fire seasons.

For the reasons discussed earlier we use the Niño 3.4 index

(<http://www.cpc.ncep.noaa.gov/data/indices/sstoi.indices>) as our measure of the state of ENSO. We also examined fire relationships with the IOD, calculated by comparing the SST in eastern and western Indian Ocean (the positive phase corresponds to relatively cool conditions in the east and warm in the west, and vice versa;

<http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCDC/.ERSST/.version4/.IOD/.C1961-2015/.iod/index.html>). The seasonal means of these indices were calculated from 1982-2015 (due to longer period available) and the 1999-2015 seasonal deviation from the mean calculated. It was not necessary to standardise or detrend the indices as there was far less variation than for rainfall and no significant trends over the time period. The correlations were calculated as with rainfall described above.

3 Results and discussion

3.1 Australian fire trend

Figure 1 shows that there was a decrease in Australian fire levels from 2001-2010 using the AF product. This was followed by an upsurge in 2011 and 2012, which is what *Giglio et al.* [2013] found when using the BA product over Australia. This indicates that the inconsistencies seen with burned products in many parts of the world [e.g. *Roy et al.*, 2008] are perhaps not so significant in Australia. The *Dutta et al.* [2016] annual increase (in 2007-2013 bush-fire frequencies) is apparent visually (but not statistically significant) However, note that, when seen in the context of the two earliest years of our record (2001-2002), the 2007-2013 period was not particularly fire abundant and hence their analysis started from a low base. The ‘climate shift’ of 2011 onwards coined by *Dutta et al.* [2016] seems to have been short lived and 2013-2015 fire levels have returned to the

2002-2010 levels.

Figure 1 also highlights the seasonal variability over Australia, with the spring (SON) being the most fire abundant season (48% of all fires), followed by winter (21%), and then similar frequencies occurring in the seasons of summer (16%) and autumn (15%). Summer is the only season that displays a statistically significant 2001-2015 trend ($p < 0.05$). The sign of the summer trend is at odds with the findings of *Dutta et al.* [2016]. To explore these apparent discrepancies we have broken up the Australian region into smaller areas and conducted further analysis.

3.1.1 Australian regional fire trends

Australia covers a range of climatic zones and studies have split the continent up by these zones or by state boundaries [e.g. *Dutta et al.*, 2016]. Here we break down the analysis further, into regions of high fire levels to give us a deeper understanding of the spatial diversity. We also stratify the analysis by state as shown by the map and boxes in Figure 2, to allow comparisons with other studies and highlight differences between state governments' fire management and policies. Boxes 1-6 represent each State and Territory (with New South Wales (NSW), Victoria (Vic) and the Australian Capital Territory combined) and boxes 7-14 represent fire abundant/more populated/different land use areas (see Australian Government Department of Agriculture and Water Resources <http://www.agriculture.gov.au/abares/aclump/land-use>). Australian fire levels are decreasing or stable, with high temporal and spatial variability. Eastern NSW (Figure 2 - box 12) has the strongest decreasing trend, especially during the winter season, where it is significant at the 0.1% level (represented by the black box marked 'JJA'). Summer and autumn experience a statistically decreasing trend whereas spring is not experiencing a trend. Victoria (Vic)/NSW combined (box 5) also shows a decreasing tendency, but only in the spring and summer seasons. *Nicholls and Lucas* [2007] found that the Tasmanian BA declined between 1952-2003, which seems to have continued (box 6) and, as with Vic/NSW, this occurs only in spring and summer. The other region experiencing a significant annual trend is south-east Queensland, again mainly in the spring and summer seasons. These decreasing fire regions are relatively highly populated and have very strongly significant fire weekly cycles (Figure S4), so one could speculate that the declining trends

seen here are due to improved fire management, reducing the size and duration of bush fires. We will return to this aspect in Section 4.

These results indicate that the positive trend of the *Dutta et al.* [2016] study were strongly influenced by their specific short period of record, which began during the ‘millennium drought’ [*van Dijk et al.*, 2013]. For the purpose of comparing our fire levels with the fire index used by *Dutta et al.* [2016], we here conduct an annual trend analysis for the shorter 2007-2013 period (highlighted by asterisks in Figure 2). The only region which experienced a strongly statistically significant increase during their temporal period was Western Vic (indicated by the asterisks in box 13). This region displayed no significant annual or seasonal trend (except for an increase in spring $p < 0.1$) throughout the 2001-2015 period due to 2001-2006 experiencing comparatively frequent fires.

In addition to anthropogenic influences on fire regimes, climate conditions such as drought and periods of increased precipitation are well known to impact on fuel loads (e.g. heavy rain often results in more plant growth). This, in turn, strongly influences future fire seasons [*Spessa et al.*, 2005; *Harris et al.*, 2014], especially in the less managed northern region.

3.2 What does precipitation tell us of future Australian fires?

Numerous studies have found links with climate variables such as temperature, rainfall and relative humidity in Australia, linked to ENSO and the IOD [e.g. *Harris et al.*, 2008, 2014; *O’Donnell et al.*, 2011]. On a larger scale, *Chen et al.* [2016] found that sea surface temperature can be used to forecast the interannual variability of BA in many regions of the globe by means of climate controls on fuel continuity, amount, and moisture content. We build on this approach and explore in detail how the climate conditions affect current and future fire levels, by considering the synchronous and lagged fire season behind the precipitation/ENSO/IOD season. There are complex relationships between precipitation characteristics leading up to a given fire season (varying with times of year), therefore, unlike previous studies, we investigate all seasons consolidated together as well as individual seasonal effects on following fire levels, also analysing seasons outside of the natural fire season.

3.2.1 All-season relationship between precipitation and fires

Figure 3 and Table 1 show the relationship between seasonal Australian precipitation and seasonal fire levels for all seasons considered together, i.e. all 59 full seasons from 2001-2015. Figure 3a and b shows the time series of standardised seasonal anomalies for both fire and precipitation. There is a clear (inverse) relationship, as seen in other studies [e.g. *Verdon et al.*, 2004; *Spessa et al.*, 2005; *O'Donnell et al.*, 2011; *Harris et al.*, 2014]. A negative concurrent (lag 0) season correlation (more precipitation associated with fewer fires) throughout Australia exists as shown by the scatter plot in Figure 3c, and has a p-value of < 0.01 (also highlighted in the top left square of Table 1). By lag 3 (Figure 3d), the sign has changed and reflects a significant (to the 1% level) positive relationship (more precipitation associated with more fires 3 seasons later and vice versa), and a stronger positive (0.1% level) is seen by lag 5 (Figure 3e). Table 1 presents the full picture for Australia as a whole, northern Australia ($< 22^{\circ}\text{S}$), southern Australia ($> 22^{\circ}\text{S}$) and the regions investigated in Figure 2.

This sign for significantly correlated seasons changes when the fire levels is lagged (compared to precipitation) by 3 seasons, with the exception of Vic and NSW, which maintain a negative relationship for longer and Tasmania remains relatively neutral after the initial negative. This absence of a lagged correlation is also the case with other smaller regions throughout Australia. Over the larger regions, namely the whole country and larger states and territories, the fire season and the precipitation during the 3-5 previous seasons have a very strong positive relationship. Part of the reason is likely due to vegetation growth during the higher precipitation periods, providing more fuel for fires 3-5 seasons later [*O'Donnell et al.*, 2011]. The southern states, with larger populations, place a higher priority on managing fuel loads, as mentioned, which is possibly the reason we don't see this positive relationship. This is supported by the highly significant weekly cycles in fires in these regions (figure S4). *Felderhof and Gillieson* [2006] and *Harris et al.* [2008] found a strong positive relationship exists between fire indices in northern Australia and the precipitation characteristics of the previous 9-15 months, which is consistent with our results. In Vic, *Harris et al.* [2014] found that climate variables had an influence on future fire levels, which is

what we find here to a limited extent (1 season lag). They state that other factors such as local weather conditions, terrain, agriculture type, fire frequency and fire management (planned burning and suppression of wildfires) play more of a role than in other fire-affected regions of Australia.

Previous studies [e.g. *Harris et al.*, 2008, 2014] have found the climate of specific seasons that had the most impact on the fire levels in the following season, although the nature of the association differs throughout Australia and depends, in part, on the climate and persistence of precipitation characteristics [*Simmonds and Hope*, 1997]. In parts of south-west WA, periods of high fire levels tended to occur during drought conditions that followed wet and cool conditions, particularly in spring and summer of the preceding year, linked with ENSO phase and growth of ephemeral plants with subsequent drought conditions promoting fuel drying [*O'Donnell et al.*, 2011]. In contrast, Tasmania's fire levels are more closely related to the concurrent precipitation conditions, especially in summer, meaning that a wet summer means lower fire levels [*Nicholls and Lucas*, 2007].

3.2.2 Seasonal relationships between precipitation and fires

We have seen that the nature of synchronous and lagged relationships depend strongly on the time of year, which is likely to be associated with vegetation characteristics. This observation indicates that considerable insights can be gained by performing seasonal analysis of precipitation – fire level associations, so individual seasonal analyses were conducted across Australia.

Table 2 shows the relationship between Australian precipitation and seasonal fire levels changes throughout the year and across the continent taking the base precipitation seasons as MAM, JJA, SON and DJF. The negative concurrent season correlation seen in Table 1 throughout Australia is strongest in the summer (Table 2 – bottom right). It is also highly significant in Vic/NSW and Tasmania in spring and throughout winter (Table 2 – top right). The negative winter relationship in these regions is probably due to prescription burning requiring relatively dry weather during this typically wet time of year. The change in sign when the fire lag is over 2 seasons (Table 1), is mostly influenced by spring precipitation which has a major effect on the following year's fire season (Table 2 – bottom left), again with the exception of Vic and NSW, which maintain a negative

relationship for longer.

The precipitation characteristics from March-May (MAM- Table 2 – top left) give little indication of the activity in the following fire seasons, except for the JJA season of the following year, highly significant for the whole continent in the Spearman tests. There is a weak (5% and 10% level) negative concurrent season relationship in some southern areas and Queensland. The precipitation during winter (Table 2 – top right) only significantly affected the current and following and mainly in southern areas. This indicates that the winter precipitation has little influence over the following fire seasons, as *O'Donnell et al.* [2011] found for south-west WA (SWWA). Table 2, however, shows us that in this area, winter precipitation is significantly correlated with fire levels in the following autumn. SON precipitation (Table 2 - bottom left) tells us most about the following fire seasons. There is a strong negative concurrent relationship in some southern areas (Vic, NSW, Tasmania and SWWA). The strong positive correlations seen in Table 1 are likely mainly influenced from the SON precipitation, where we see very high correlations at 3-5 season lag. This is in contrast to *Harris et al.* [2008] who found the strongest relationship for northern Australia to be the June–October fire levels and the preceding precipitation of November–March.

Harris et al. [2014] found that for Vic, low precipitation totals through September– November tended to be followed by more fires in the subsequent November-March fire season, which is what we see here for VIC/NSW combined. Summer (Table 2 – bottom right) unsurprisingly has strong negative concurrent relationship, this being the main fire season over southern Australia. WA's summer precipitation gives a very strong indication of what the following spring/summer/Autumn fire season will be like, especially in the north of the state. This backs up the work of *O'Donnell et al.* [2011] who found that major fire years tended to occur during drought conditions that followed wet and cool conditions in spring and summer of the preceding year in parts of SWWA (though our signal is not as strong here as in the north). *Nicholls and Lucas* [2007] found that the major controlling factor for fire levels in Tasmania was the concurrent precipitation conditions, meaning that a wet (dry) summer means lower (higher) fire levels. This is marginally significant in Table 2 (bottom right).

Our analysis highlights the potential for using the spring precipitation data to forecast the severity of the concurrent (lag 0) spring fire levels and risk in the southern states. It also provides strong links with the following June-February in broader areas of the continent, likely to be due to vegetation memory.

3.3 What does Niño 3.4 tell us of future Australian fires?

Short-term (from a season to a year or two) climate variations are often linked to large-scale atmospheric circulation drivers such as ENSO and the IOD. These are known to affect temperature, humidity, cloud cover, vegetation, fuel loads and the fire regime of the following months and seasons [e.g. *Verdon et al.*, 2004; *O'Donnell et al.*, 2011; *Harris et al.*, 2014]. El Niño generally results in low precipitation for the Australian continent (with the opposite occurring for La Nina).

3.3.1 All-season relationship between Niño 3.4 and fires

Table 3 indicates that when Niño3.4 is correlated with the concurrent and lagged fire levels, temporal and spatial patterns are generally similar with precipitation, as would be expected. There are some differences however. Southern areas have a positive concurrent relationship between Niño 3.4 phase and fire levels, then neutral beyond 1 season lag, however, unlike for precipitation, most northern areas have no concurrent or one seasons lag relationship. From a 3 season lag onwards, the correlation becomes very strongly negative for the whole country, other than Vic/NSW and Tasmania, structures we have already seen for precipitation. This strongly negative relationship lasts until lag six seasons.

For Vic, *Harris et al.* [2014] found that ENSO indices have significant relationships with Victorian fire levels, though not as robustly as other Australian regions, which seems to be the case here, with a significant concurrent relationship, but is not significant beyond one season lag. In NSW, positive ENSO episodes was found to increase the proportion of days with a high, or greater than high, fire danger rating [*Verdon et al.*, 2004], which is consistent with our positive concurrent and following season correlation.

3.3.2 Seasonal relationships between Niño 3.4 and fires

We have seen that precipitation depends strongly on the time of year and we know that precipitation is highly influenced by ENSO. Therefore, it is of value to conduct a similar seasonal analysis of Niño3.4 – fire level relationships. Table 4 shows this relationship throughout the year and across the continent. The predictability barrier [Schepen *et al.*, 2012] is highlighted by MAM (Table 4 – top left) not providing much information about present and future fire seasons (even less than precipitation). Again, the general patterns are in agreement with the precipitation anomalies, with some differences. Harris *et al.* [2008] found a negative ENSO JJA relationship with the June-October fire season of the following year, which we also find in Table 4 (top right). This inconsistency with precipitation is not surprising given that during this time ENSO has the least effect on Australian climate [Schepen *et al.*, 2012], but it is unclear why positive (negative) ENSO during winter would mean an inactive (active) fire season during the following spring without seeing this in the precipitation.

It could be argued that the fact that the Niño3.4 has a high autocorrelation with the following season (Figure 4a) influences the apparent spring relationship with precipitation, which is highly significant for many areas (Table 2 – top right). When JJA Niño3.4 seasonal anomalies are correlated with the following SON's (Figure 4b – top right), this argument is supported, with an extremely high r-value (0.94). The annual and seasonal autocorrelations of Niño3.4 are negligible for the 4 and 5 season lag before going negative by a 6-season lag, which indicates that this is not the cause of the strong 4-5 season lag correlations (Tables 3 and 4).

The strength of the statistical significance test results indicates that we can potentially use the Niño3.4 JJA anomalies to predict the fire severity of the following year, even if the precipitation at this time does not exhibit a clear signal. SON (Table 4 – bottom left) provides an insight into subsequent fire levels but not as much as the precipitation. A negative relationship is apparent in the north for the following JJA and positive in the south (Vic/NSW and Tasmania) for the concurrent and following fire season (DJF), consistent with precipitation activity. DJF (Table 4 bottom right)

Niño 3.4 is only weakly related to fire levels compared to SON and far less for concurrent seasonal fire levels when compared to the precipitation of the same seasons. The negative relationship of 3-5 season lag is evident but only marginally significant. *Nicholls and Lucas* [2007] found a link to summer ENSO (positive relationship between SST and fire levels) in Tasmania, especially the SST of the Coral Sea, which we don't see for Niño 3.4 here.

These results indicate that ENSO has a highly statistically significant relationship with fire levels in Australia and there is potential to use ENSO indices (such as Niño3.4) to forecast the severity of future fire seasons in different areas of the continent. Precipitation gives the best indication of the severity of the current and following fire levels except for JJA where the ENSO index of Niño3.4 may be more useful for predicting the severity of the following year's fire season.

3.4 IOD

The relationship between the IOD and fire levels was very weak except in spring (Table 5 –bottom left). The other seasons (Table 5) and composited seasons (not shown) do not show any coherent significant patterns. The IOD spring relationship has been highlighted in the literature and *Cai et al.* [2009] stated that major fire events in south-eastern Australia have been linked to the occurrence of positive IOD events and the associated unusually dry and warm spring conditions. We see this positive relationship with concurrent season throughout the continent except for Queensland as we would expect. The IOD is also known to affect SWWA future fire season and we find that spring IOD not only has the concurrent positive relationship seen in other parts of Australia, but also significantly impacts (negatively), so the following winter and subsequent summer fire pattern. *O'Donnell et al.* [2011] were surprised when they did not find this relationship in their research, indicating that the study was potentially over too small an area to pick up a robust signal.

Overall, the spring IOD provides more information for concurrent fire conditions than precipitation or Niño3.4. It is therefore an important index to consider alongside precipitation and ENSO when forecasting/assessing fire levels.

4 To what extent can identified trends be affected by clouds and anthropogenic activities?

There are a number of factors which can contaminate the AF information that we have used here. One of these is clouds, which can block the satellite's line-of-sight, and hence variability in cloud properties could give rise to apparent variability of fires. A second important factor in the interpretation of fire variability and trends is the extent to which anthropogenic fire activity may be obscuring the natural fire regime. We address these issues in Supporting Information as we summarise below.

We have analysed cloud fraction data to determine whether variability and trends identified in the AF product are associated with corresponding temporal behaviour in the cloud fraction. We can confirm that the trends found in AFs are not significantly affected by the temporal variability of clouds (see Figures S1 and S2 and Text S1).

In a similar vein we have also investigated the weekly cycles of AF for each season over Australia as a whole, and these are shown in Text S2 and Figure S3. Over this broad area no significant weekly cycle is identified in summer. This indicates that the summer decreasing AF trend seen in Figure 1 is not associated with anthropogenic influences (although we are unable to assess other anthropogenic influences, such as long-term changes in land use). By contrast, on a regional scale, the decreasing fire regions (Figure 2) are in relatively highly populated and have very strongly significant weekly cycles (Figure S4), so one could speculate that the declining trends seen here are due to improved fire management, reducing the loads, size and duration of bush fires. This is in accord with the weekly cycles seen throughout Australia during autumn (Figure S3), as this season is when most of the decreasing trends occur (Figure 2 – box 4-6 and 11-12). However, there are some regions with very strong weekly cycles and no statistically significant declining trend, for example SWWA (Figure 2 – box 7). Generally the areas not well correlated with the climate drivers and rainfall for 3-5 seasons lags (tables 1-5), mainly in the south as mentioned, have strong weekly cycles, suggesting that anthropogenic fuel management is the dominant factor for these regions.

5 Conclusions

We use a moderate-resolution 2001-2015 series of daily satellite-based global active fire (AF) data to comprehensively examine recent variability and trends across Australia. We also investigate the roles played by rainfall and by large-scale atmospheric structures (namely El Niño–Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD)), in influencing fire levels in different regions.

Using robust statistical tests, we show, for the first time, Australian fire levels are decreasing or steady, with high temporal and spatial variability. Spring is the most fire abundant season (48% of all fires), followed by winter (21%), summer (16%) and autumn (15%). Summer is the only season which displays a statistically significant 2001-2015 trend ($p < 0.05$), which is decreasing. Eastern NSW has the strongest decreasing trend, especially during the winter season. We have shown that anthropogenic influences have contributed to these decreases. Other significantly decreasing areas are Vic/NSW, Tasmania and South-east Queensland. Precipitation and ENSO have highly statistically significant relationships with fire levels in Australia. Southern areas have a positive concurrent relationship between Niño 3.4 phase and fire levels, then no statistical relationship beyond 1 season lag. Northern areas have a no relationship until 3 seasons lag when it becomes very strongly negative. The spring IOD provides more information for concurrent fire conditions than precipitation or Niño3.4, but not for any other period. The relationships are highly variable across Australia and differ significantly throughout the year. However, our results suggest there is considerable potential for skilful forecasts of future season fire levels based on current and previous precipitation activity and large scale climate driver indices, namely, Niño3.4 and the IOD. The results of our analysis will be of benefit to regions of Australia in particular seasons, over which there is significant potential to forecast future fire levels.

We will build on this present work with the next generation of fire detection products. As mentioned earlier, improvements have been made to the fire detection algorithm and swath-level product, part of the Collection 6 land-product reprocessing (commenced in May 2015), which will reduce some of the limitations of Collection 5 such as fires obscured by smoke [Giglio *et al*, 2016] and false alarms from solar reflection [He and Li, 2012].

Acknowledgements

The authors thank Kevin Ward of NASA's Earth Observatory for helping with the initial data download (available at http://neo.sci.gsfc.nasa.gov/view.php?datasetId=MOD14A1_M_FIRE) and Andrew King for useful discussions. Parts of this research were made possible by funding from the Australian Research Council Grant DP140102855. We thank the Bureau of Meteorology, the Bureau of Rural Sciences, and CSIRO for providing the Australian Water Availability Project data.

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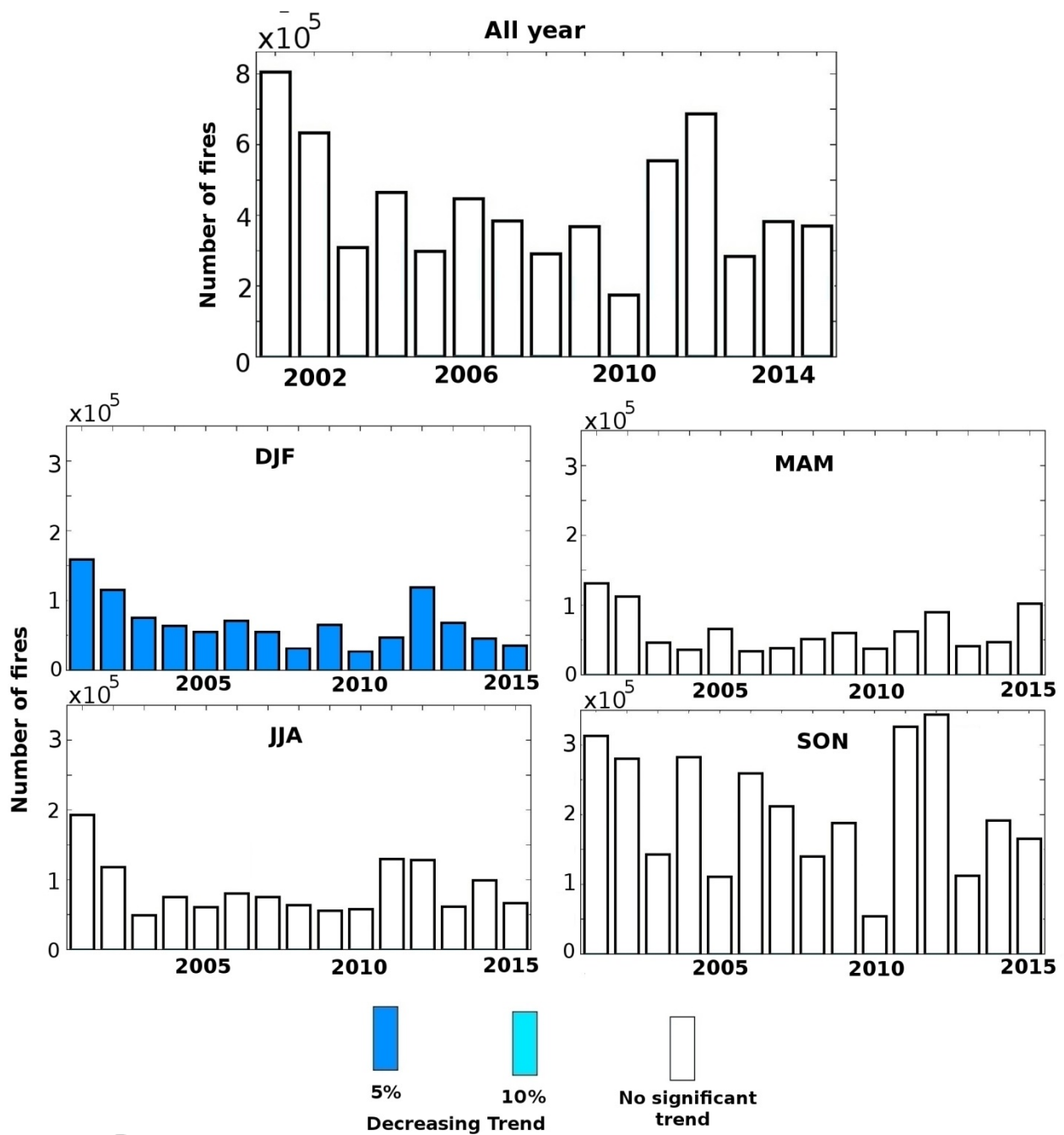


Figure 1 - Time series 2001-2015 of Australian fire counts. Trends in annual and seasonal AF count totals with significance levels indicated, with use of color bars and boxes. December–February (DJF), March–May (MAM), June–August (JJA) and September–November (SON).

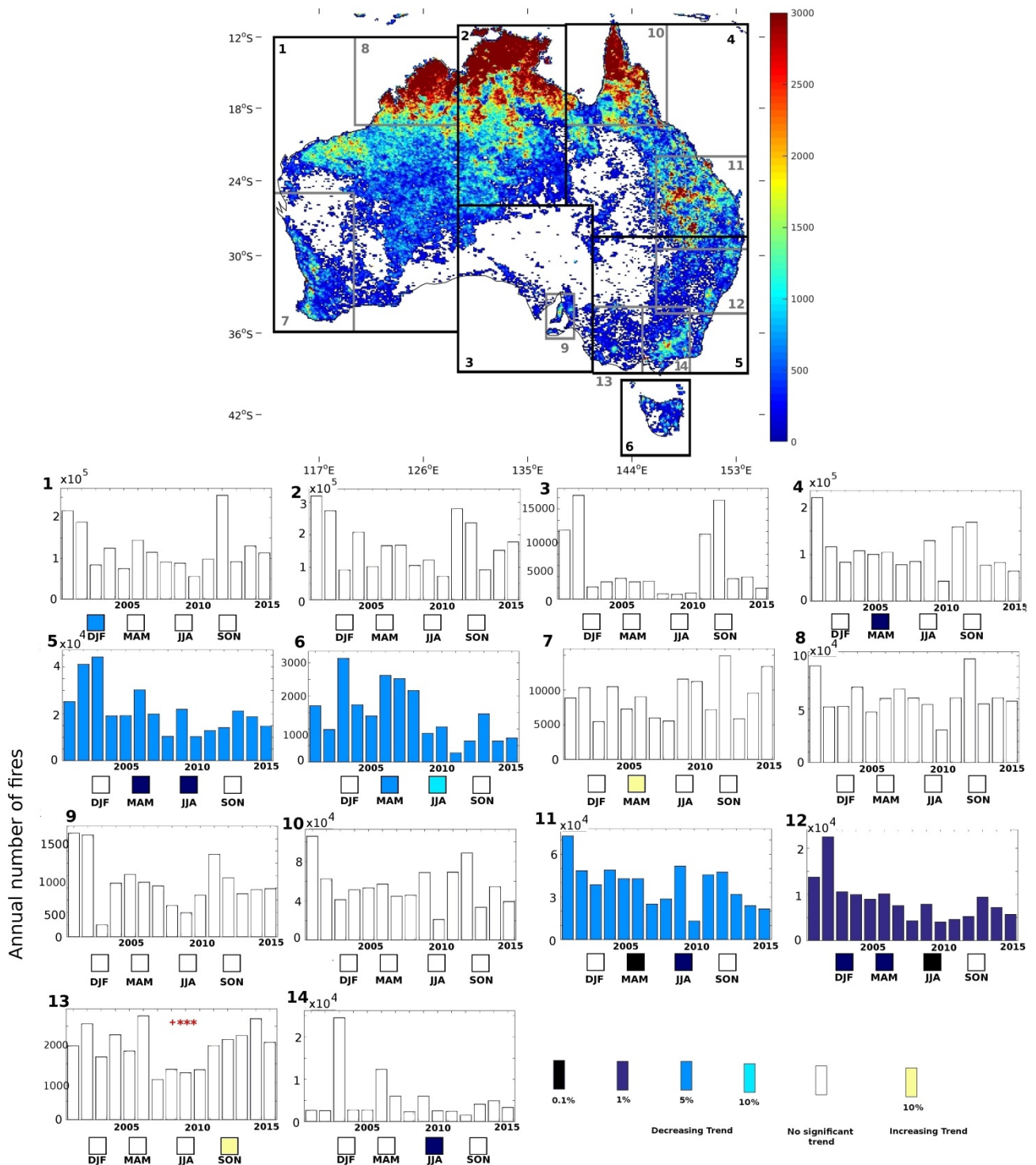


Figure 2 – Top panel, total counts of active fire 2001–2015 (1000 km^2)⁻¹. Lower panels, fire time series and statistics in the 14 key regions of Australia over 2001–2015. For each region the histogram displays the annual AF count total, and the color of the bars denotes whether (and at what confidence level) the trends are significant (the color code is presented in the boxes at the bottom-right of the Figure). The statistical significance of seasonal trends also is indicated in the four small

squares (from left to right for December -February, March-May, June-August and September-November below each histogram, using the same color coding as above.. (Note that the scales on the time series differ for the various regions.) Asterisks indicate whether the regional annual time series, considered over the shorter 2007-2013 period, exhibit significant (positive and negative) trends (+/-* = 10% level, +/-** = 5% and +/-*** = 1%).

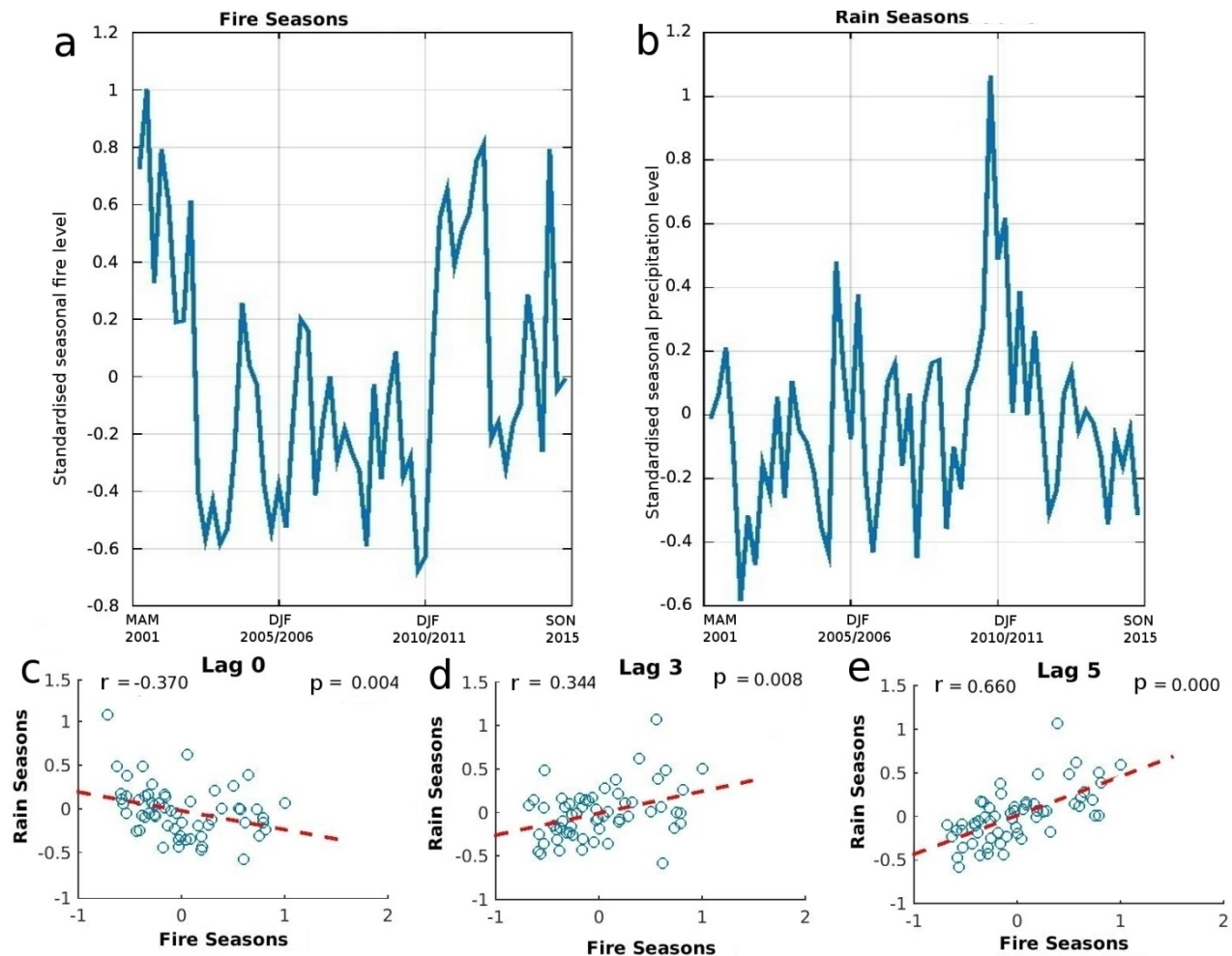


Figure 3 – Time series of standardised Australian fire and precipitation for each complete 2001-2015 season, from March-May 2001 to September-November 2015. The correlations of these are then shown for 0 (directly correlating the corresponding points on the time series), 3 and 5 season lags, with p- and r-values from the Spearman rank correlation tests displayed. Note – these values match up with the corresponding lags in the ‘Australia’ line of Table 1.

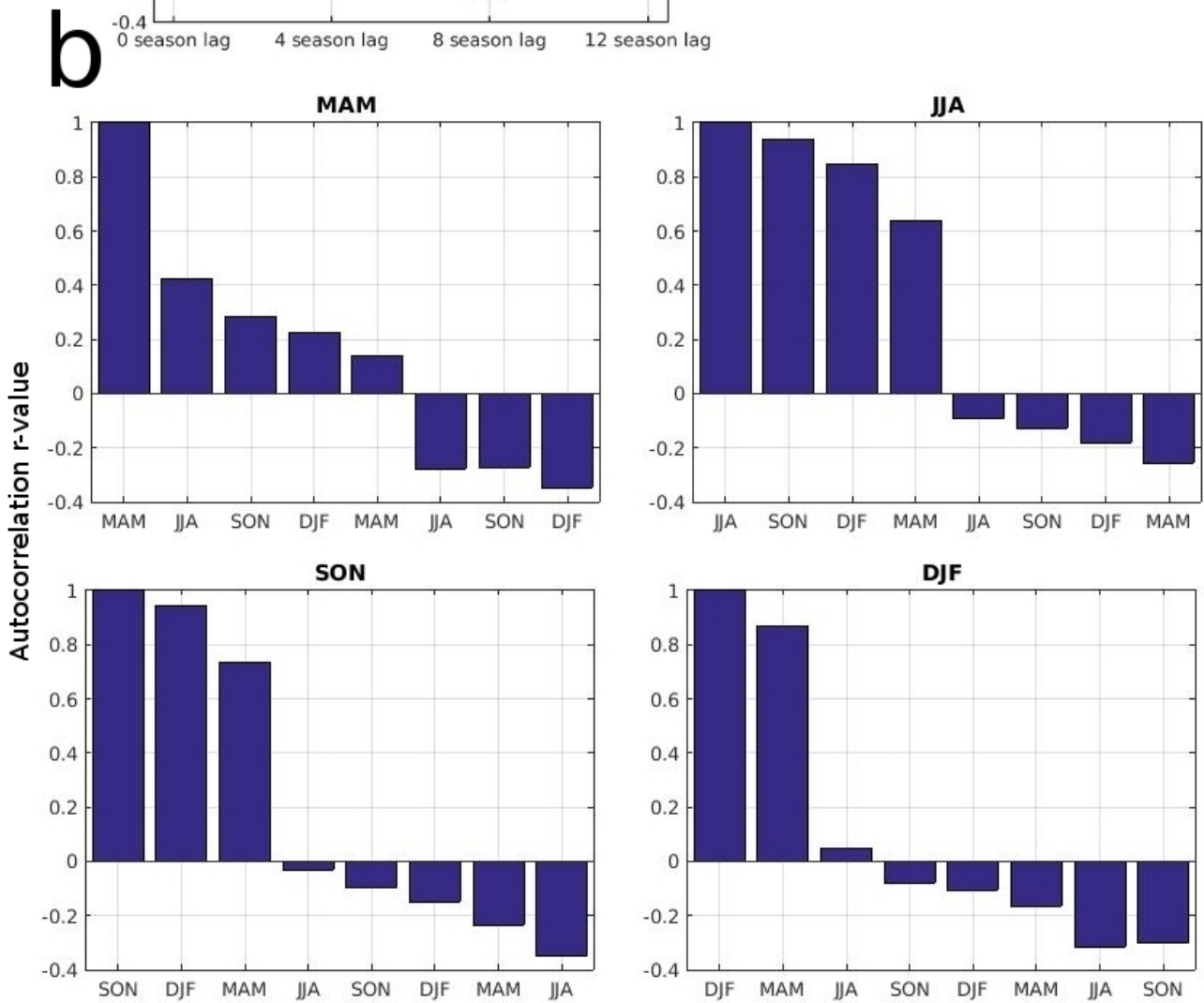
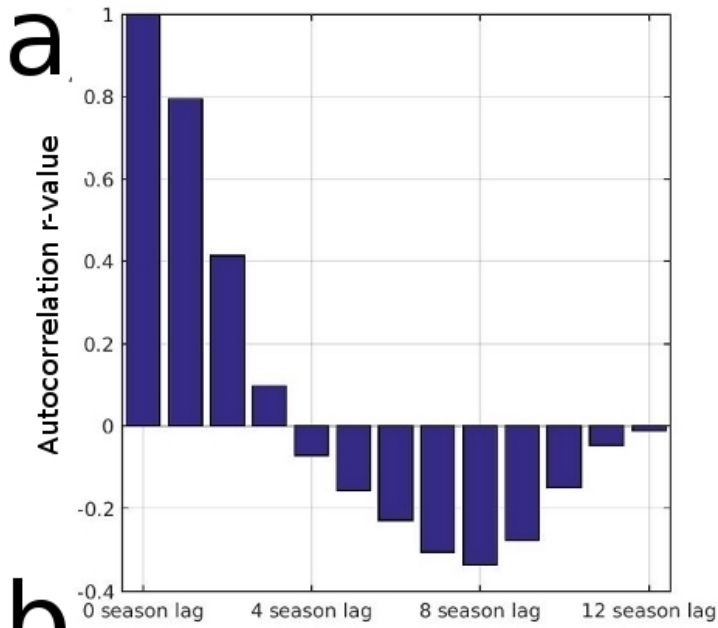
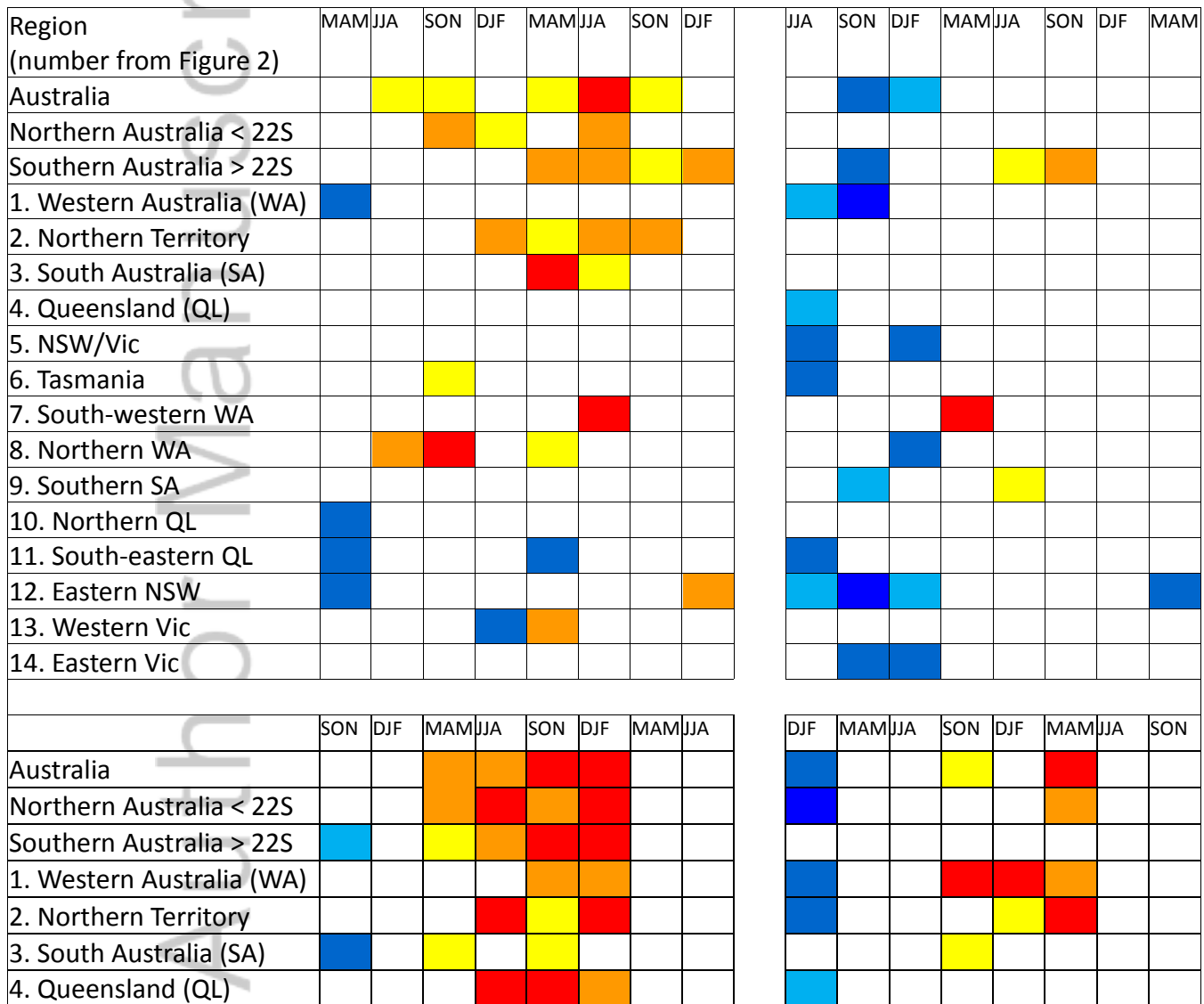


Figure 4 – a) 1982-2015 Niño3.4 seasonal anomaly autocorrelation b) as with (a) but for each season

Region (number from Figure 2)	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
Australia	-.37	-.06	.22	.34	.45	.66	.32	.21
Northern Australia < 22S	-.29	-.06	.17	.36	.34	.55	.32	.18
Southern Australia > 22S	-.26	-.15	.18	.43	.48	.50	.41	.29
1. Western Australia (WA)	-.44	-.22	.09	.34	.40	.46	.34	.07
2. Northern Territory	-.26	.04	.22	.45	.39	.51	.28	.07
3. South Australia (SA)	-.16	-.19	.16	.45	.41	.31	.26	.11
4. Queensland (QL)	-.42	-.14	.04	.25	.18	.35	.22	.16
5. NSW/Vic	-.56	-.31	-.21	-.13	.05	.04	.09	.22
6. Tasmania	-.55	-.29	.10	-.03	.12	.06	-.01	-.04
7. South-western WA	-.39	-.13	.25	.00	.20	.11	-.08	.05
8. Northern WA	-.12	.03	-.05	.26	.21	.23	.24	.06
9. Southern SA	-.09	-.30	.19	.28	.30	-.19	-.08	.00
10. Northern QL	-.41	-.13	.16	.31	.22	.42	.26	.16
11. South-eastern QL	-.44	-.41	-.13	.22	.15	.12	.09	.16
12. Eastern NSW	-.58	-.38	-.20	-.08	-.05	.16	-.06	.13
13. Western Vic	-.20	-.12	.07	-.18	.07	-.10	.15	.20
14. Eastern Vic	-.37	-.30	-.21	-.08	.07	-.16	.08	.16

Table 1: Regression analysis r-values (from the Spearman rank correlation) of standardised fire season anomaly with standardised precipitation total anomaly for all 59 full 2001-2015 seasons for all regions of

Australia (see Figure 2) with All Australia and Northern (<22°S) and Southern (>22°S) included. Lag 0 refers to concurrent season and the lag 1-7 refers to the lag of the fire season behind the precipitation season. Confidence levels for positive correlations are denoted by yellow (10%), orange (5%), and red (1%). Those for negative correlations are indicated by light blue (10%), mid-blue (5%), and dark blue (1%). Correlations that fail to reach the 10% significance level are displayed in grey.



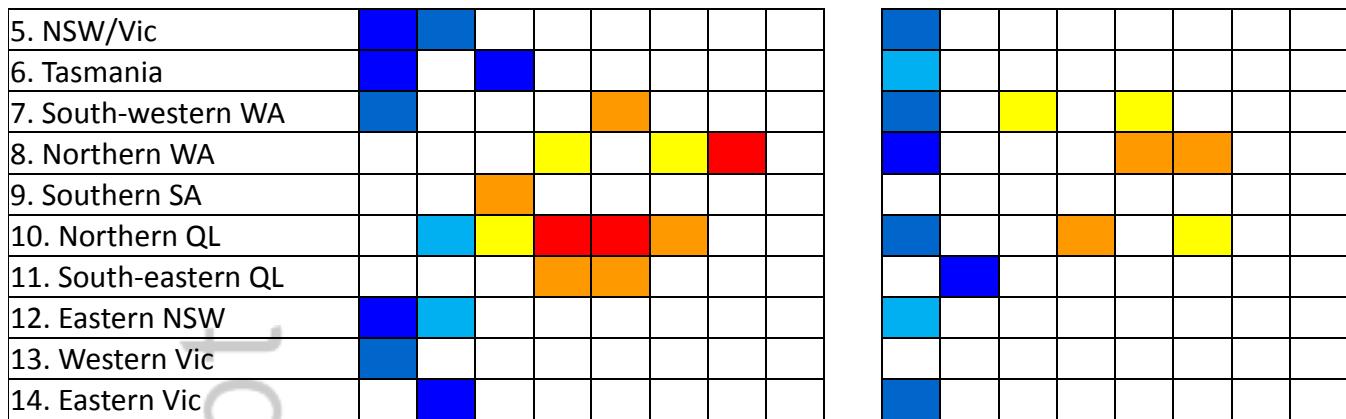


Table 2: As for Table 1 but here the correlations (between precipitation standardised anomalies vs AF seasonal anomalies - synchronous and subsequent seven seasons) are calculated for the individual seasons. MAM (top left), JJA (top right), SON (bottom left) and DJF (bottom right). The magnitude of the r-values required for significance are .44, .52 and .66 for the 10%, 5% and 1% confidence levels, respectively.

Region (number from Figure 2)	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
Australia	.25	.07	-.23	-.48	-.55	-.49	-.34	-.27
Northern Australia < 22S	.18	-.01	-.27	-.47	-.51	-.48	-.36	-.24
Southern Australia > 22S	.36	.16	-.18	-.50	-.59	-.45	-.27	-.29
1. Western Australia (WA)	.28	.12	-.09	-.32	-.40	-.44	-.40	-.28
2. Northern Territory	.15	-.03	-.28	-.40	-.40	-.39	-.29	-.20
3. South Australia (SA)	.07	-.04	-.23	-.33	-.31	-.18	-.06	-.10
4. Queensland (QL)	.21	.16	-.14	-.41	-.57	-.49	-.31	-.23
5. NSW/Vic	.49	.36	.17	-.06	-.17	-.17	-.11	-.21
6. Tasmania	.21	.26	.28	.22	.09	.11	.30	.25
7. South-western WA	.27	.11	-.02	-.09	-.22	-.13	-.12	.02
8. Northern WA	.07	.00	-.12	-.29	-.39	-.47	-.39	-.18
9. Southern SA	.06	.03	-.12	-.15	-.15	.03	.13	.01

10. Northern QL	.27	.16	-.16	-.39	-.48	-.41	-.33	-.31
11. South-eastern QL	.27	.25	.00	-.25	-.41	-.31	-.12	-.12
12. Eastern NSW	.50	.38	.23	.01	-.09	-.05	-.03	-.22
13. Western Vic	.25	.15	.04	-.01	.08	.02	-.03	-.13
14. Eastern Vic	.31	.19	.04	-.08	-.10	-.11	.02	-.01

Table 3 - As with Table 1 but for Niño3.4 SST seasonal anomalies correlated with standardised fire season totals.

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Region (number from Figure 2)	MAM				JJA				SON				DJF			
	MAM	JJA	SON	DJF	MAM	JJA	SON	DJF	JJA	SON	DJF	MAM	JJA	SON	DJF	MAM
Australia																
Northern Australia < 22S																
Southern Australia > 22S																
1. Western Australia (WA)																
2. Northern Territory																
3. South Australia (SA)																
4. Queensland (QL)																
5. NSW/Vic																
6. Tasmania																
7. South-western WA																
8. Northern WA																

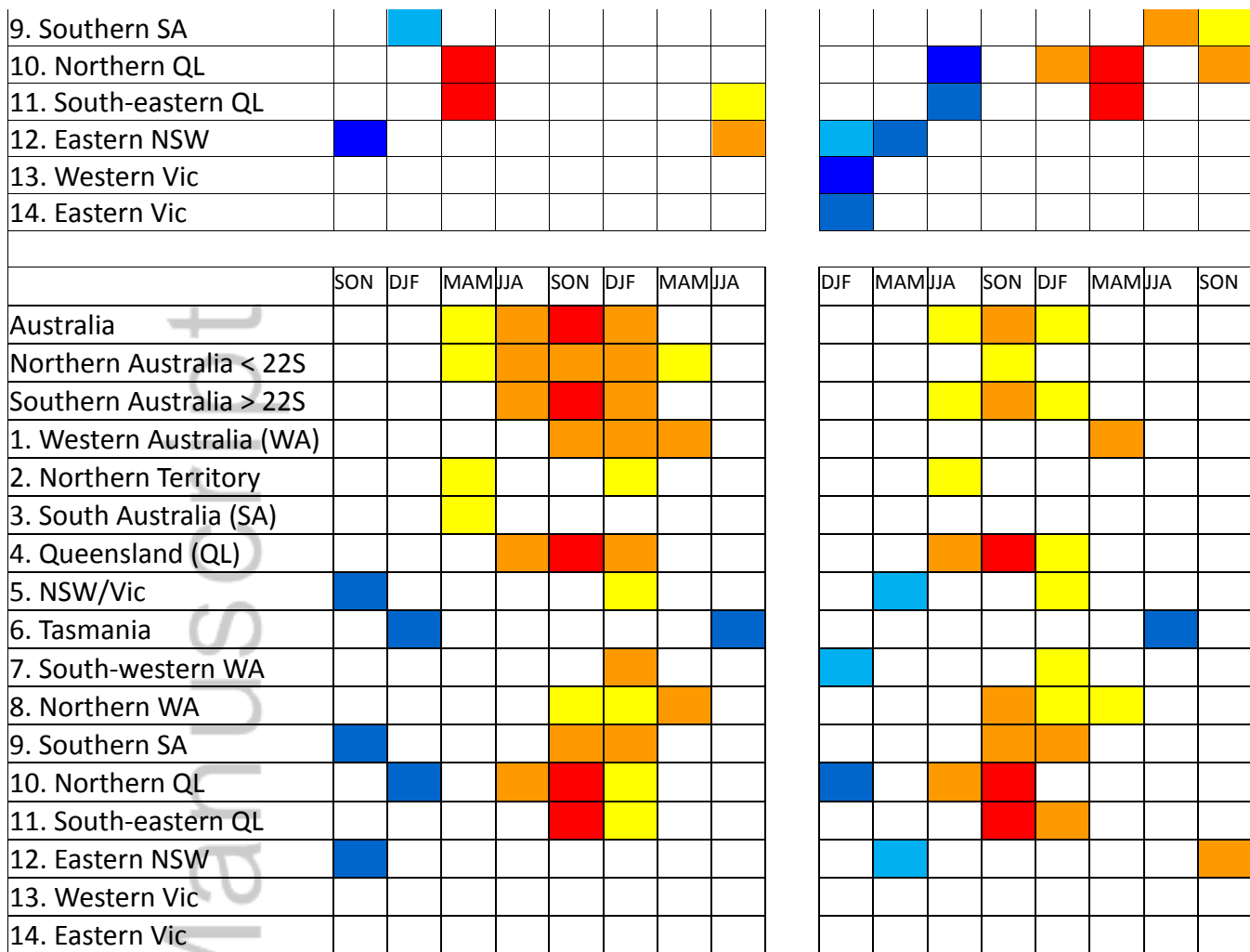


Table 4 - As with Table 2 but for Niño3.4 SST seasonal anomalies correlated with standardised fire season totals. The magnitude of the r-values required for significance - .45, .50 and .64 for 10%, 5% and 1% confidence levels respectively.

Region (number from Figure 2)	MAM	JJA	SON	DJF	MAM	JJA	SON	DJF	JJA	SON	DJF	MAM	JJA	SON	DJF	MAM
Australia																
Northern Australia < 22S																
Southern Australia > 22S																
1. Western Australia (WA)																

2. Northern Territory								
3. South Australia (SA)								
4. Queensland (QL)								
5. NSW/Vic				Orange				
6. Tasmania							Orange	
7. South-western WA								
8. Northern WA								
9. Southern SA					Blue			
10. Northern QL								
11. South-eastern QL					Red			
12. Eastern NSW	Red							
13. Western Vic								
14. Eastern Vic				Yellow				

	Blue		Light Blue					
				Yellow				
				Blue				
Yellow							Blue	
		Yellow						
	Blue							

	SON	DJF	MAM	JJA	SON	DJF	MAM	JJA
Australia	Blue							
Northern Australia < 22S	Light Blue							
Southern Australia > 22S	Blue		Yellow	Yellow				
1. Western Australia (WA)	Blue							Orange
2. Northern Territory	Blue			Orange		Yellow		
3. South Australia (SA)	Blue	Blue	Yellow					
4. Queensland (QL)								
5. NSW/Vic	Light Blue							
6. Tasmania		Blue	Light Blue					
7. South-western WA	Blue			Orange		Orange		
8. Northern WA								Yellow
9. Southern SA	Blue		Orange		Yellow			
10. Northern QL				Yellow				
11. South-eastern QL				Yellow				
12. Eastern NSW								
13. Western Vic	Blue							
14. Eastern Vic	Blue	Blue						

DJF	MAM	JJA	SON	DJF	MAM	JJA	SON
					Blue		
		Light Blue			Blue	Blue	
					Blue	Blue	
		Orange				Orange	Yellow
					Yellow		
Orange					Blue		
Orange							
		Orange					

Table 5 - As for Table 2 but for IOD correlated with standardised fire season totals The magnitude of the r-values required for significance - .46, .52 and .64 for 10%, 5% and 1% confidence levels respectively.