Drought Propagation and Recovery Behaviours Across 407 Australian Catchments

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Key Points:

- Drought propagation and recovery behaviours for a large sample of catchments under varied climatic zones within Australia are investigated.
- Propagation and recovery lag relationships are well-defined for shorter droughts but are increasingly indefinable for longer droughts.
- Propagation (TP) and recovery lags (TR) depend on drought severity with shorter TP to milder droughts and longer TR to milder droughts.

Abstract

A reliable understanding of linkages between meteorological, hydrological and agricultural droughts (MD, HD and AD respectively) is crucial to building resilience and planning for future climate changes. Despite Australia being prone to severe droughts, lagtimes of propagation (and recovery) from meteorological to hydrological and agricultural droughts across its large hydroclimatic regions are not well understood. Therefore, we investigate the characteristics of drought propagation and recovery time lags for droughts of four timescales and a combination of drought onset and cessation criteria in 407 unregulated catchments within six major precipitation zones across Australia. We find that the propagation and recovery lags are dependent on climatic conditions, drought criteria and timescales. The average propagation times from MD to HD across Australia varied from 0.8 to 1.7 months for monthly timescales, increasing to 2 to 4.5 months for 12-monthly timescales. The corresponding recovery lagtimes were 1.3 to 3.7 and 1.7 to 7.5 months respectively. Similarly, the average propagation times from MD to AD ranged from 0.9 to 1.9 months for monthly timescales, increasing to 0.8 to 5 months for 12-monthly timescales. The corresponding recovery lagtimes were 0.7 to 2.8 and 0.3 to 9.4 months respectively. For droughts of smaller timescales, propagation and recovery lags are linearly correlated with recovery lagtimes consistently greater than the propagation times. As the timescale increases, these relationships weaken suggesting effects of other catchment attributes (e.g. groundwater contributions) on lag relationships. Notably, recovery lagtimes are generally longer for the high-yielding catchments in eastern Australia compared to the other regions.

Key words: Drought propagation, Drought recovery, Drought Lagtime

Plain Language Summary

The primary focus of the research is to investigate the time delay between the occurrence of the lack of precipitation (meteorological droughts) and its subsequent impact on river flow (hydrological drought) and soil moisture (agricultural drought). Understanding these delays is crucial for drought planning and management. This study uses observed precipitation, river flow, and satellite-based soil moisture data spanning over 40 years across six major precipitation zones within Australia. The delays between drought types (meteorological, hydrological, and agricultural) vary depending on the specific location within Australia. The criteria used to define the onset and end of droughts, as well as the drought duration, also influence the observed delays. The average delay from meteorological to hydrological or agricultural droughts increases with longer timescales. For example, monthly droughts have shorter delays (0.8 to 1.7 months), while 12-month droughts have longer delays (2 to 4.5 months). Similarly, shorter droughts have shorter recovery times, while longer droughts have longer recovery times. For shorter timescale droughts, there is a clear relationship between the delays with end delays consistently greater than the start delays. However, as droughts become larger and more prolonged, the relationship weakens, suggesting the influence of other catchment attributes.

1 Introduction

Communities in Australia and around the world are facing prospects of more frequent and severe droughts (Ahmadalipour et al. 2019; Bureau of Meteorology & CSIRO 2018; Cook et al. 2015; Leng et al. 2015; Spinoni et al. 2018). Frequent prolonged and extreme droughts such as the Federation Drought of 1895 to 1902, World War II drought during 1937-1945, and others during 1957-1964, 1965-1968, 1982-1983, 1997-2009 (the Millennium Drought) and 2017-2019 affect both the socioeconomic and natural ecosystems of rural and regional Australia (BOM, 2015, 2020a, 2023; Kiem et al., 2016). Therefore, the ability to quantitatively predict the onset and end of droughts is valuable for managing water resources and lessening impacts on farm output thus helping those communities to cope and recover (Fuentes et al., 2022; Ho et al., 2021). Furthermore, enhancing drought resilience through improved drought management and planning is even more critical under a changing climate, demanding a deeper understanding of drought propagation.

Droughts typically are initiated by a deficiency in precipitation, potentially followed by reduced river flow, diminished reservoir storage, lower groundwater levels, and decreased soil moisture (Tallaksen & Van Lanen, 2004; Van Loon, 2015). Consequently, linkages between the three distinct types of droughts, such as meteorological droughts (MD), hydrological droughts (HD) and agricultural droughts (AD) are of interest to hydroclimate researchers and to water resources managers (e.g., Barker et al., 2016; Gu et al., 2020; Han et al., 2019; Ho et al., 2021; Huang et al., 2017; Keyantash & Dracup, 2002). It is worth noting that both the onset and cessation lagtimes between MD and HD/AD are important variables in studying the resilience or resistance of a biospheric region to lack of precipitation. These lagtimes provide valuable insights for drought preparedness, response and mitigation. Increasingly, research efforts have been put into the development of methods for quantifying the propagation time (i.e., onset lagtime) from meteorological drought events to hydrological or agricultural drought events (e.g., Liu, et al., 2019, Apurv et al., 2017; Guo et al., 2020; Shin et al., 2018). The recovery lags (i.e., cessation lagtimes) between MD and HD/AD however are less considered. There are only a few studies quantitively investigating the relationships between propagation and recovery lags and how they change for droughts of different timescales and from one climatic region to another based on different drought criteria (Palmer, 1965; Heim, 2002; Sattar et al., 2019; Xu et al., 2019; Gu et al., 2020). To date, there is no available study to examine how the propagation and recovery lags behave across Australia.

Therefore, the primary objectives of this study are to investigate the behavior of drought propagation and recovery and their interrelationships across diverse climate regions in Australia, considering various severity levels and time scales of drought events. For this, we have developed standardized drought indices for 407 catchments across Australia, using observed precipitation, streamflow, and soil moisture data to identify meteorological, hydrological, and agricultural drought events respectively. An event-based approach is then introduced to quantify both the propagation time (TP) and recovery time (TR), aiming to address the following knowledge gaps:

(i) How does the propagation time or recovery time of an MD to an HD or AD event vary across climatic regions in Australia?

(ii) What is the relationship between propagation time and recovery time for drought events of varying time scales and across diverse climatic regions?

(iii) How do propagation time and recovery time differ between drought events of varying severity?

These objectives collectively guide our exploration of drought dynamics and provide insights into their temporal and spatial characteristics across Australia, contributing to enhanced drought management under more extreme climates. This paper is organized as follows. Section 2 describes the hydroclimatic data and methods for calculating drought indices and probability distribution functions. Results are given in Section 3 followed by a discussion in Section 4. Section 5 provides the conclusion.

2 Data and Methods

2.1 Hydrometeorological Data

Daily precipitation and streamflow data from the Australian Bureau of Meteorology's 407 Hydrologic Reference Stations (HRS) from 1971 to 2018 were used to develop the standardised precipitation and streamflow indices. The HRS catchments are unregulated and largely unimpaired with areas ranging from 4.5 to 232,850 km^2 and a median of 392 km^2 (BOM, 2020b).

They are located across Australia, covering the six major precipitation zones (Table 1). Water years starting in October were used for summer, summer-dominant and arid zones; May for winter and winter-dominated zones, and January for the uniform precipitation zone. Daily precipitation and streamflow were aggregated to their monthly total for all catchments.

Table 1 Details of precipitation zones across Australia

Precipitation zones	**Number of catchments**	**Mean annual precipitation**	**Mean annual evapotranspiration**
Arid (Ad)	14	340	1737
Summer (Sm)	90	1041	1432
Summer-dominated (Sd)	56	1356	1533
Uniform (Un)	64	854	1323
Winter (Wt)	121	915	1541
Winter-dominated (Wd)	62	964	1539

Soil moisture data from the European Space Agency's (ESA) Climate Change Initiative for the period 1978 to 2018 were used to develop standardised soil moisture indices for identifying agricultural drought events. The dataset has a spatial resolution of 0.25° × 0.25° and reflects the soil moisture content (SMC) of the maximum 5 cm depth in a dimensionless volumetric unit (m^3/m^3). The gridded surface daily SMCs were aggregated to generate the monthly catchment-mean soil moisture for the 407 catchments for further processing.

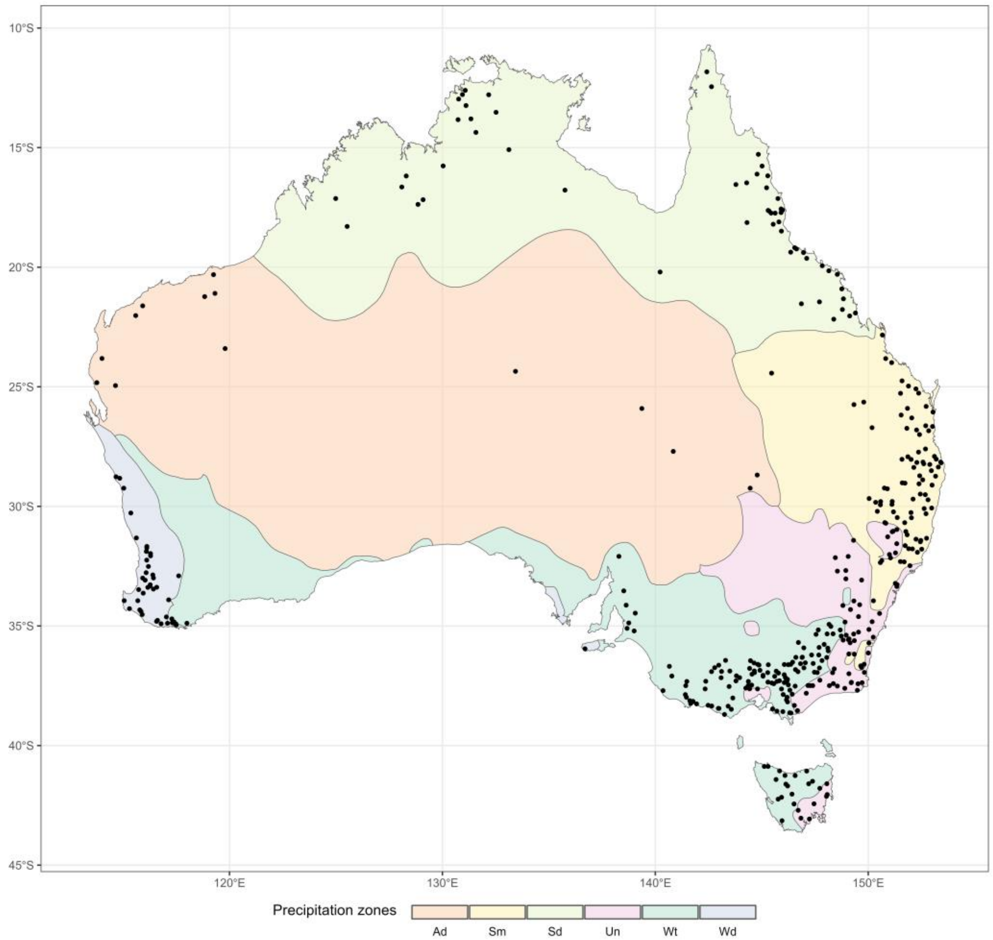

Figure 1 Locations of the 407 Hydrologic Reference Stations in Australia. The precipitation zones arid (Ad), summer (Sm), summer-dominated (Sd), uniform (Un), winter (Wt) and winter-dominated (Wd) are shown in the background.

2.2 Identifying Drought Events Using Standardised Drought Indices

To determine the characteristics of drought events such as onset, cessation, duration and intensity, various standardised drought indices have been introduced for use in the literature (e.g., Chen et al., 2018, 2019; Farahmand & AghaKouchak, 2015; Heim, 2002; Kwon et al., 2019; Mishra, 2020; Rivera et al., 2017; WMO, 2012; Zhao et al., 2017). The standardised drought indices facilitate the comparison of droughts across different regions and timescales. Among all standardised indices, the Standardised Precipitation Index (SPI), which relies solely on readily available precipitation data, is widely adopted and also recommended by the World Meteorological Organization (WMO, 2012) to characterise meteorological droughts. Meanwhile, the Standardised Streamflow Index (SSI), derived from streamflow data, is predominantly used to examine the spatial and temporal patterns of hydrological droughts (Shukla & Wood, 2008;

Vicente-Serrano et al., 2010, 2012). For agricultural drought, the Standardised Soil Moisture Index (SSMI), computed using soil moisture data, is generally employed as soil moisture directly impacts crop growth in farmland areas (Holzman et al., 2014; Yang et al., 2021).

A crucial step in deriving SPI, SSI, or SSMI is to determine a probability distribution function (PDF) that optimally fits the raw precipitation, streamflow, or soil moisture data. This process typically requires a dataset with a minimum length of 30 to 50 years. (Agnew, 2000; Agnew & Chappell, 1999; McKee et al., 1993; Wu et al., 2005). To our knowledge, the best probability distribution functions of the hydroclimatic variables have not been reported for the HRS catchments across Australia. Accordingly, we investigate probability distributions of precipitation, streamflow and soil moisture at different time scales for each individual catchment prior to standardising their time series. For precipitation, PDFs include normal, two-parameter gamma, Weibull and lognormal are considered. For streamflow, the PDFs considered include normal, gamma and Weibull as reported in the literature (e.g., Bowers et al., 2012; Shukla & Wood, 2008; Vicente-Serrano et al., 2012; Zaidman et al., 2002). Since many Australian streams are intermittent with frequent zero annual flow, we did not use methods that use log transformation. The normal, gamma, lognormal and Weibull distributions are used to fit the observed soil moisture data to calculate the SSMI. The goodness-of-fit of each probability distribution is calculated using Akaike and Bayesian Information Criteria separately at each location to decide the best-fitted PDF.

With the derived best distribution function, all hydroclimate variables are standardised to calculate z-scores using the approximations of Abramowitz and Stegun (1964). The detailed steps in calculating the z-score are well described (Kumar et al., 2009; Vicente-Serrano et al., 2012; Zarch et al., 2015) and are not repeated here. Drought indicators calculated using longer timescales help understand the slow responding systems such as regional groundwater level, while those for shorter timescales are useful in understanding the effects of precipitation deficit on grasslands, agricultural crops and streamflows. Therefore, SPI and SSI were calculated separately at timescales of 1, 3, 6 and 12 months with the help of the best-fitted probability distribution function, described above, for each catchment. The SSMIs of similar timescales were calculated for the period 1978 to 2018 due to data availability.

Drought events are then identified based on the time series of SPI, SSI and SSMI derived using a set of given criteria (Figure 2). The onset of a drought event is the first day in a window of time series with standardised drought indices below a given critical value, while cessation of a drought event is the last day with a value above the critical one. Different critical values can represent different severities of the drought event identified. In general, critical values of - 0.5, -1.0 and -1.5 are used to define mild, moderate and severe drought events respectively (e.g., WMO 2012).

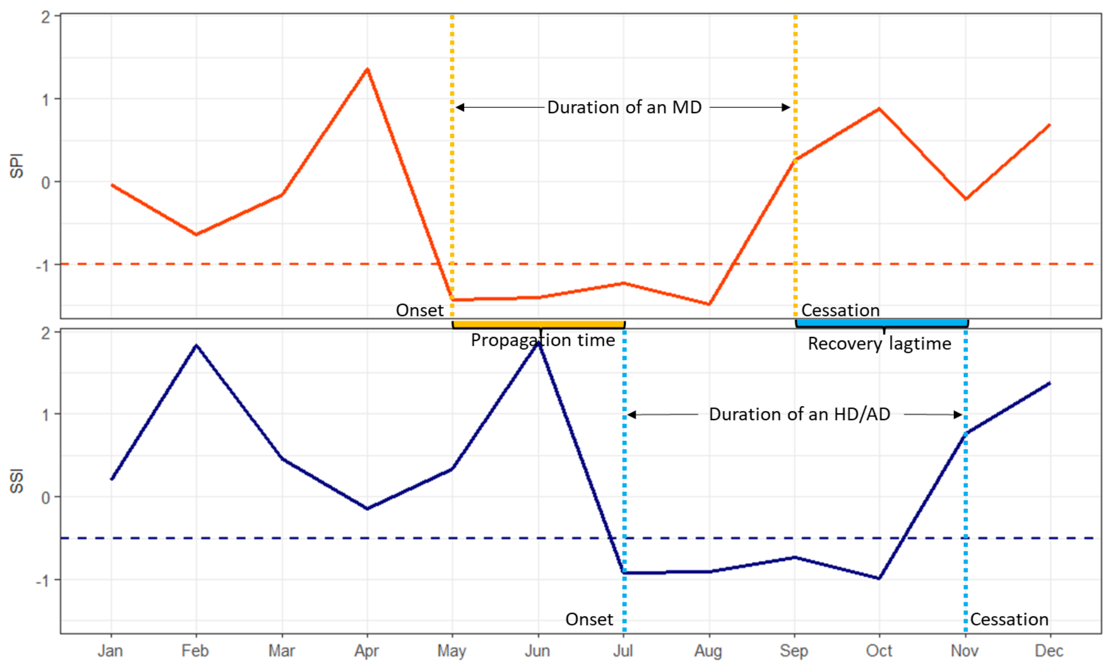

Figure 2 Schematic diagram showing the runs of the time series of SPI and SSI assuming SPI < -1.0 and SSI <- 0.5 as the criterion for the onset and cessation of meteorological drought and hydrological droughts respectively.

2.3 Determining Propagation and Recovery Laglimes

We introduce an event-based approach to determine the propagation time (TP) and recovery lagtime (TR) between related drought events as illustrated in Figure 2. The propagation time of MD to HD/AD is defined as the time it takes for an MD to initiate an HD or AD, represented by the time difference between the onset of an MD and an HD/AD event. Similarly, the recovery lagtime between MD and HD/AD is defined as the time it takes for an HD/AD to come to the predrought condition after its initiating MD has ceased, represented by the time difference between the cessations of an MD and an HD/AD event. It is worth noting that the onset and cessation of a drought event, and hence TP and TR, could be affected by the critical values set for drought event identification and temporal variability of the hydroclimatic variables as well.

At the catchment scale, hydrological (or agricultural) drought can be viewed as being triggered by meteorological drought. However, hydrological drought (or agricultural drought) does not necessarily start (or cease) immediately after the onset (or cessation) of meteorological drought due to characteristics of the hydrological cycle in the catchment. Hydrological droughts incorporate the effects of several catchment properties, such as land cover, topography, geology and river network structure, and respond to MD in different ways across regions (Stoelzle et al., 2014; Van Lanen et al., 2013). Consequently, MD events of varying intensity can lead to differing extents and intensities of HD or AD in different catchments (Tallaksen et al., 2009). In this study, to ensure consistency and robustness, the event-based approach has been developed with the following underlying principles or assumptions:

- Onset of an HD/AD event cannot be earlier than its initiating MD event;
- Onset of an HD/AD event cannot be n-month later than the cessation of its initiating MD event (n=3 is used herein);
- An MD event can trigger an HD/AD with the same or different severity;
- An MD event is related only to the first HD/AD event within the duration of the MD. For MD events without subsequent HD/AD, the propagation time and recovery lagtime are assumed to be infinite and are excluded for further analysis.

As different critical values can be employed to determine the onset and cessation of MD and HD/AD at varying severities, this study considers five combinations of criteria (Table 2) with the severities of drought events, with 1, 2, 3 representing mild, moderate and severe respectively (e.g. Mishra et al., 2010). These combinations characterize different aspects of drought propagation and recovery performance.

Table 2 Criteria in determining drought propagation/recovery used in this research. Subscripts in M/H/A represent the severities of drought events, with 1, 2, 3 representing mild, moderate and severe respectively.

Combinations	Meteorological Drought	Hydrological (or agricultural) Drought
M_2H_1 (or M_2A_1)	SPI < -1.0	SSI (or SSMI) < -0.5
M_2H_2 (or M_2A_2)	SPI < -1.0	SSI (or SSMI) < -1.0
M_2H_3 (or M_2A_3)	SPI < -1.0	SSI (or SSMI) < -1.5
M_3H_2 (or M_3A_2)	SPI < -1.5	SSI (or SSMI) < -1.0
M_3H_3 (or M_3A_3)	SPI < -1.5	SSI (or SSMI) < -1.5

When the criteria for the onset and end of HD (or AD) are mild (e.g. SSI < - 0.5), propagation times are shorter and the recovery times are longer. This is because a relatively small drop in streamflow can result in SSI <-0.5 (mild drought) while a large improvement in streamflow or soil moisture is needed for SSI (or SSMI) to attain a value > -0.5 (sufficiently mild drought) implying a stricter criterion for recovery. In comparison, when the criterion for the onset of HD (or AD) is severe (e.g. SSI <-1.5), propagation times are longer and the recovery times are shorter.

3 Results

3.1 Probability Distributions of Hydroclimatic Variables Across Australia

Precipitation, streamflow and soil moisture data are fitted with a range of probability distributions for all precipitation zones. The best-fit distributions for annual total precipitation, streamflow and annual mean soil moisture content follow distinct spatial patterns across the country (Figure 3a, b, c). For precipitation, the gamma distribution best fit 37.6% of catchments across Australia, followed by lognormal (35.4%), Normal (24.3%) and Weibull (2.7%). Most of the eastern catchments were fitted to lognormal, while the majority of catchments in the winter-dominated region of southwest Australia showed normal distribution. For streamflow, the gamma distribution was majority best fitted in all precipitation zones with a total of 64.3% catchments across Australia. This was followed by the Weibull (30.2%) and normal (5.4%) distributions, mostly in the high-yielding Tasmanian catchments in the winter-dominated zones.

For soil moisture content, lognormal fitted best to 42.7% catchments followed by normal (31.7%), Weibull (14.7%) and Gamma (10.8%). For the summer precipitation zone, normal distribution was best fitted to the highest number of catchments followed by lognormal, while Weibull and gamma distributions were not so prevalent.

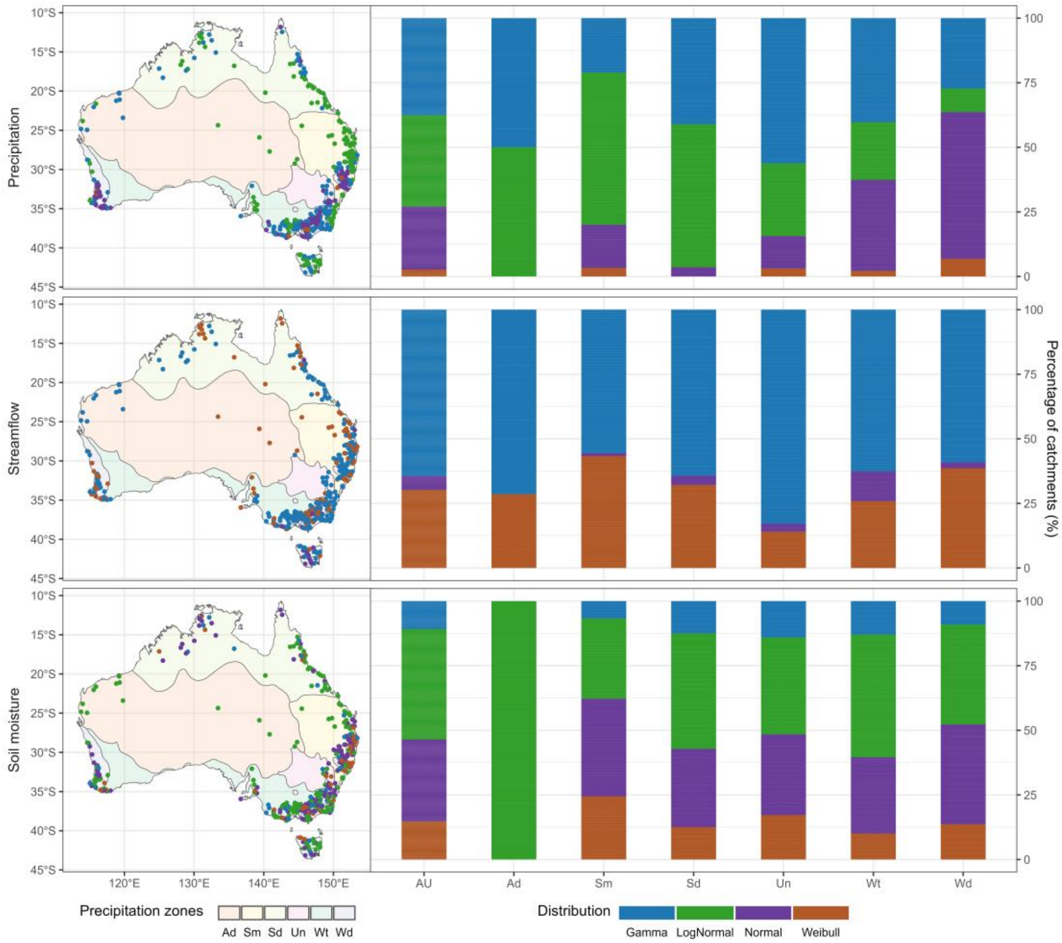

Figure 3 Spread of fest-fitted pdf across Australia and their counts in catchments (%) for (a) annual total precipitation (b) annual total streamflow (c) annual average soil moisture content.

3.2 Propagation and Recovery of Meteorological-Hydrological Droughts

Depending on drought timescales and drought criteria, the propagation time varied for the whole of Australia. The median propagation times ranged from 0.8 to 1.7 months for droughts of monthly timescale, 1.8 to 3.4 months for 3 monthly, 2.0 to 3.5 months for 6 monthly and 2.2 to 4.5 for 12 monthly droughts (Figure 4). For droughts of smaller timescales, the propagation times are also smaller, while for larger drought durations, they range from nil to about 15 months (Supplementary Figure 1).

Overall, the median recovery lags range from 1.3 to 3.7 months for droughts of monthly timescale, 2.1 to 4.5 months for 3 monthly, 1.9 to 5 months for 6 monthly and from 1.7 to 7.5 months for 12 monthly timescale. The recovery times are larger when the criteria for HD are milder and vice-versa. For example, the median recovery lags for 12 monthly droughts varied from 4.8 to 7.5 months for M_2H_1. In comparison, they ranged from 3 to 4.2 months for stricter HD criterion, i.e. M_2H_3. In general, recovery lags are generally greater than propagation lags across Australia except for when onset criteria for HD is stricter (SSI <-1.5) which required only a mild improvement in HD for the deemed recovery (Figure 4, 3rd column). Figure 4 (first column) shows larger recovery lags than the propagation time (i.e. quicker onset of HD) for mild HD onset criteria (SSI < -0.5) for all drought durations across Australia. This is because moderate-to-severe MDs can produce mild HD without much lagtime. These HDs then take longer to recover as sufficiently large precipitation is needed to recover to a mild HD state. Furthermore, these longer recovery lags are mostly experienced in winter zones indicating that these zones are prone to stay in drought for longer periods (Supplementary Figure 1).

For droughts of smaller timescales, propagation and recovery lags are better correlated and are statistically significant ($p < 0.05$). However, as the drought duration increases correlations considerably weaken suggesting a non-uniform and uncertain relationship between these lags.

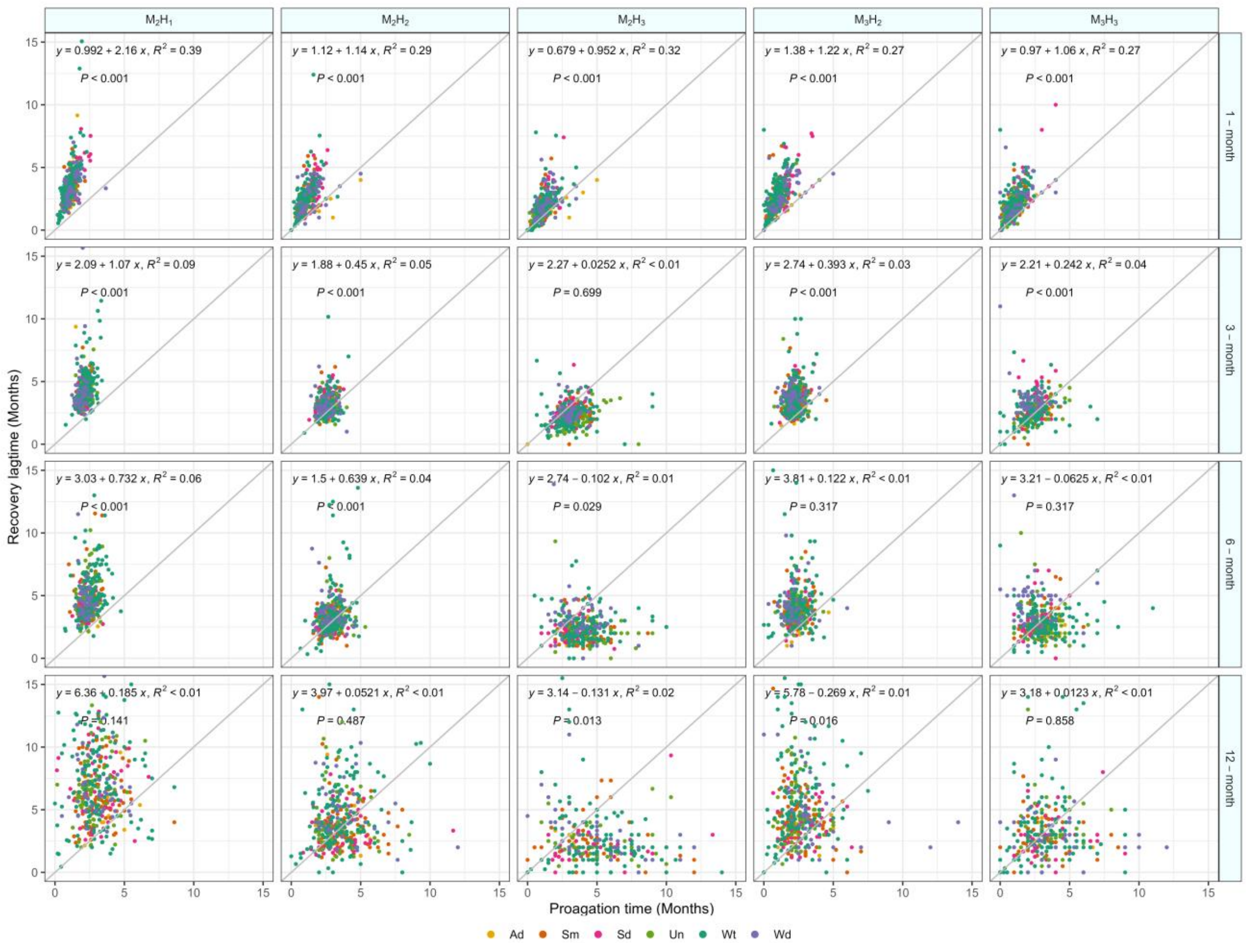

Figure 4 Propagation and recovery lag scatter plots for SPI and SSI of 1, 3, 6 and 12 monthly timescales for different drought criteria. The fitted equation, r^2 and p values shown in the plots are calculated using all 407 catchment points. See Figure 5 for r^2 for individual precipitation zones.

Further investigation shows that for shorter-duration droughts, the arid zone has the best correlations between MD and HD which are also statistically significant for all drought criteria (Figure 5). A good correlation implies a uniform response of HD to MD at the beginning and the end of droughts across all precipitation regions. However, as the drought timescales increase, correlations for all precipitation zones weaken substantially (Figure 5). No distinct variations are found in propagation times among different zones especially for larger drought durations, suggesting that drought propagation behaviours are uniform for all major precipitation zones across Australia (Figure 5).

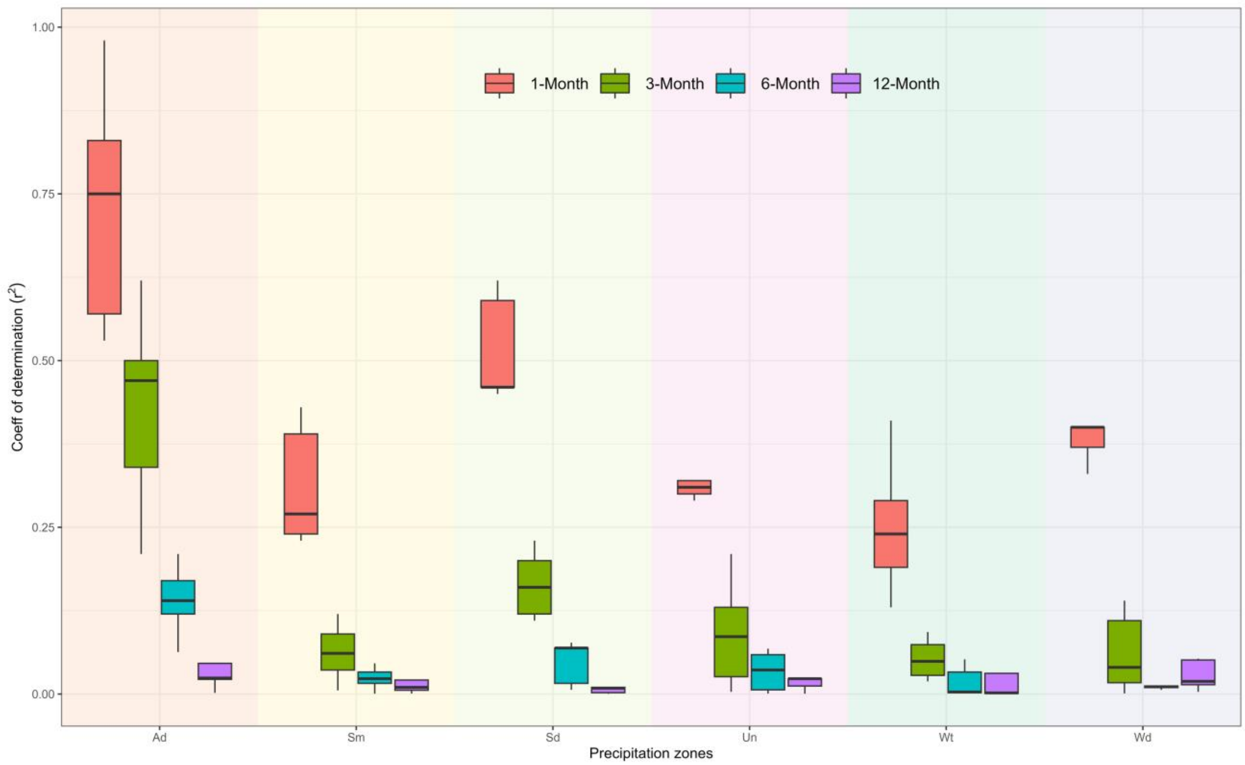

Figure 5 Coefficient of determination (r^2) showing strengths of correlation between propagation and recovery lags for hydrological droughts of different timescales. Each boxplot contains five data points for the five combinations of drought criteria (See details in Table S1). All correlations for monthly timescales are statistically significant.

3.3 Propagation and Recovery of Meteorological-Agricultural Droughts

Propagation time for smaller drought timescales do not vary much with drought criteria and range from 1 to 2 months suggesting that agricultural droughts will most likely set in within one or two months after the meteorological droughts of monthly timescale (Figure 6). For drought of 3 months timescale, the median propagation time increases, ranging from 1 to 3 months. For 6 monthly droughts, the median propagation time ranges from 1 to 4 months while the range for 12 monthly droughts is from 1 to 5 months (Supplementary Figure 2).

The median recovery lags range from 0.7 to 2.8 months for droughts of monthly timescale, 1.8 to 3.9 months for 3 monthly, 0.8 to 5.3 months for 6 monthly, and from 0.3 to 9.4 months for 12 monthly timescale. The relationships between drought criteria and recovery times are similar to those for hydrological droughts. For example, the recovery lags are functions of drought criteria and drought duration, and longer recovery lags are observed where recovery criteria are stricter (e.g. SMMI <-0.5). Propagation and recovery lags are highly correlated and are closer to the 1:1 line for droughts of smaller timescales (Figure 6) indicating that propagation times are good indicators of recovery lagtimes. However, as the drought duration increases correlations start to weaken and become non-existent for longer-duration droughts. The scatterplot, however, shows more randomness in the scatter points than those for the hydrological drought indicating a greater uncertainty in the relationship between propagation and recovery lags for agricultural drought. Recovery lags are generally slightly larger than propagation time except for cases when the criteria for the onset of AD is stricter (SSMI <-1.5) which delays the start lag but facilitates quicker recovery. In comparison, when the onset criteria for AD is mild (<-0.5), the AD can ensue quickly while taking longer to recover (Supplementary Figure 2).

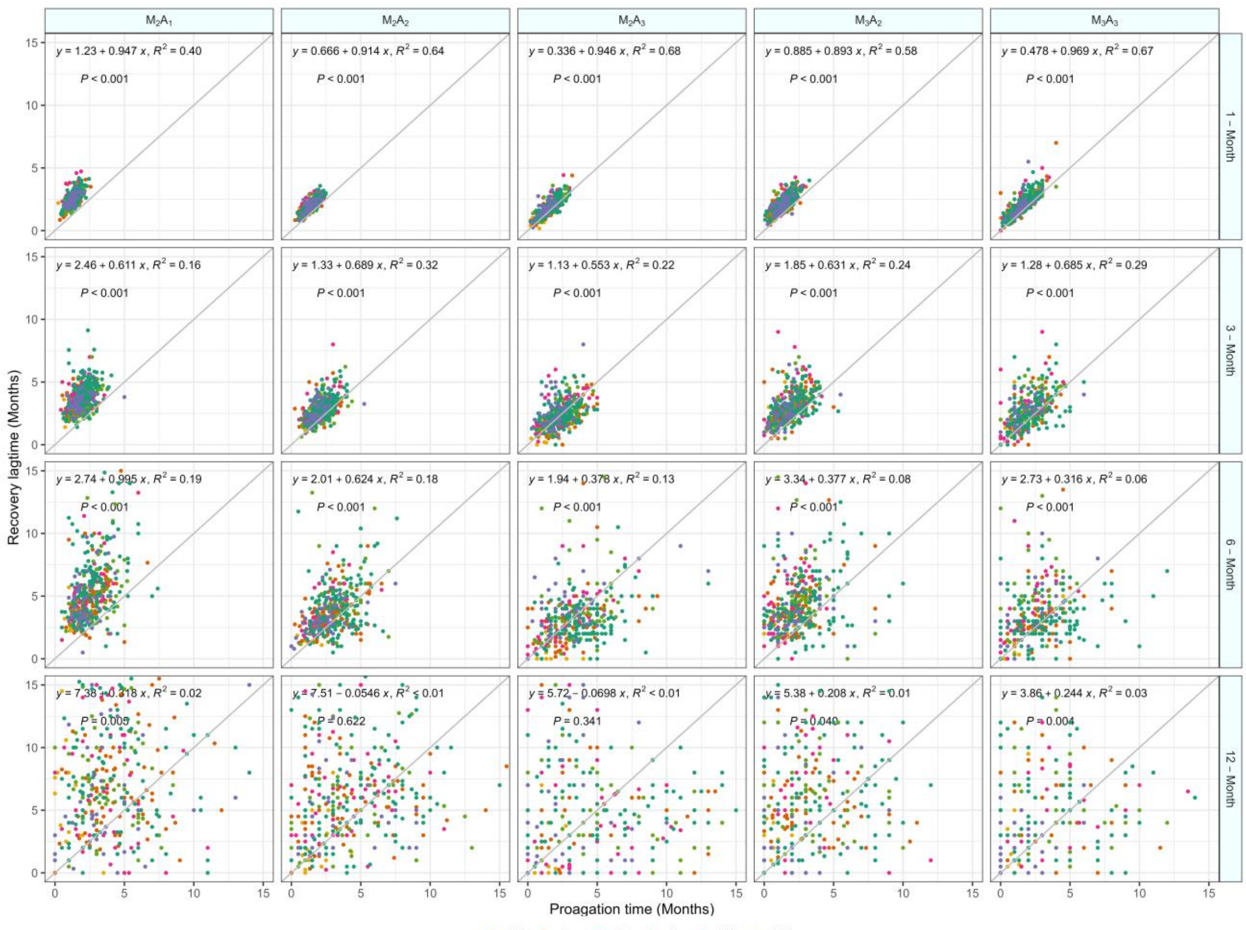

Figure 6 Propagation and recovery lag scatter plots for SPI and SSMI of 1, 3, 6 and 12 monthly timescales for different drought criteria. The fitted equation, r^2 and p values shown in the plots are calculated using all 407 catchment points. See Figure 7 for r^2 for individual precipitation zones.

The overall patterns of lag correlation between MD and AD for individual precipitation zones are similar to those for the HD (Figure 7). For individual precipitation zones, r^2 are higher and statistically significant for 1 and 3 monthly timescales and decreases as the timescale increases.

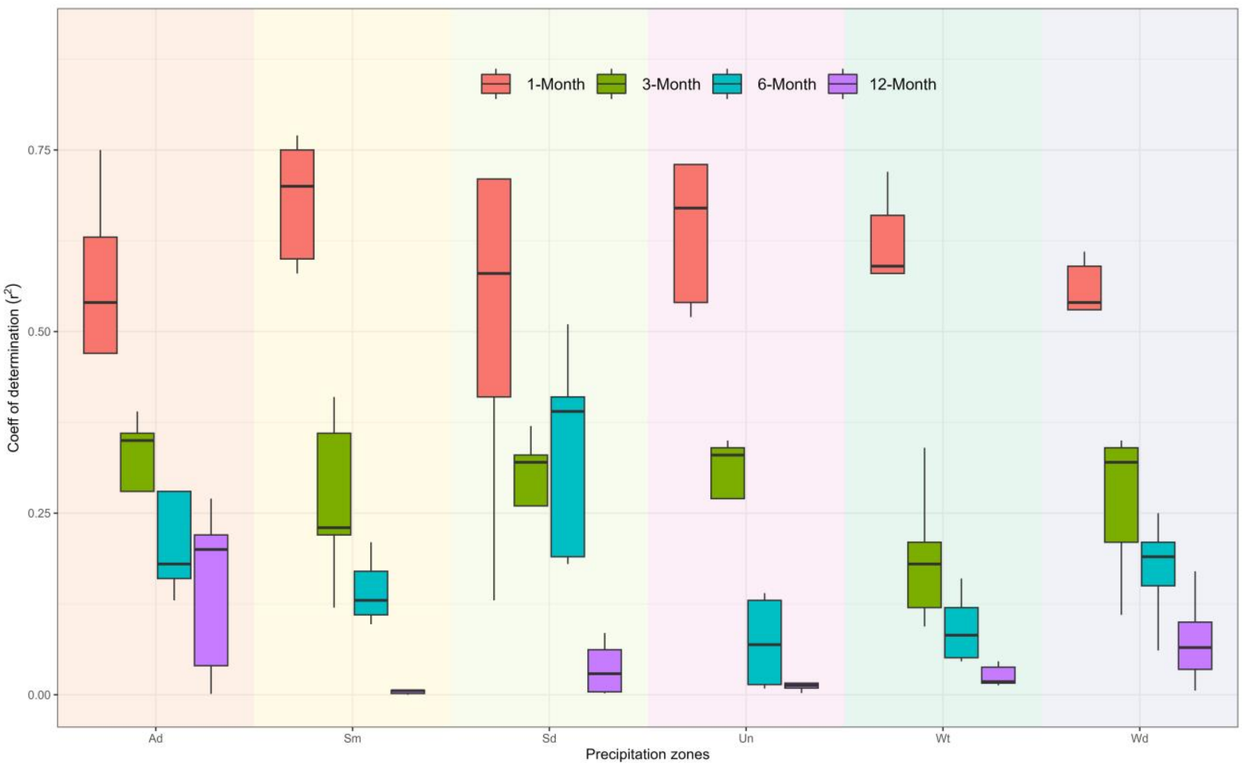

Figure 7 Coefficient of determination (r^2) showing strengths of correlation between propagation and recovery lags for agricultural droughts of different timescales. Each boxplot contains five data points for the five combinations of drought criteria (See details in Table S2). All correlations for monthly timescales are statistically significant.

4 Discussion

Drought propagation showed two distinct characteristics based on drought timescales, drought criteria and major precipitation zones in Australia. For droughts of smaller timescales, the propagation and recovery lags do not seem to depend on the criteria used to define the onset or the cessation of meteorological, hydrological or agricultural droughts. At these timescales, the magnitude of the precipitation deficit seems to be the main driver of drought propagation and recovery lagtimes. Therefore, irrespective of the criteria, the drought starts when there is a precipitation deficit. Ali et al. (2017) found the combined standardised precipitation-temperature bivariate index had strong correlations with the univariate SPI in arid and humid climatic environments for droughts of 1 to 12-month timescales suggesting the absence of precipitation as the main driver responsible for droughts, at least in the short term (Peña-Gallardo et al., 2019). For droughts of smaller timescales, recovery lags are consistently larger than propagation time most likely due to the time it takes to replenish depleted soil moisture to go back to the pre-drought conditions. Zaidman et al. (2002) found that the relationships between meteorological and hydrological droughts are less clear in Europe due to earlier years' precipitation deficits resulting in depressed regional groundwater which disproportionately enhanced the streamflow drought.

The relationships between propagation and recovery lags were good and statistically significant for droughts of smaller timescales (Peña-Gallardo et al., 2019) suggesting that recovery lags may be predicted by propagation lags across all precipitation zones. The relationship weakens as the drought duration increases indicating that for droughts of longer timescales, recovery lags are independent of propagation time and unlike for smaller timescales, they cannot be deduced from propagation time. This corroborates Lorenzo-Lacruz et al. (2013) and Sattar et al. (2019) who correlated SPI of different durations with streamflow and found a high correlation between streamflow up to 2 monthly SPI that decreased for higher durations. Lags for longer timescale droughts, however, are dependent on drought criteria as well as on the precipitation zones. Naturally, as the drought timescale increases both the propagation and recovery lagtimes increase for a given criteria and precipitation zone (e.g. Yildirim et al., 2022). For the droughts of longer timescales, virtually no relation between start and end lags is observed for all zones. The causes for the low correlation between propagation and recovery lags for long droughts can be many but the uncertainties introduced by other catchment characteristics e.g., geography, forest cover, size, regolith, and non-stationarity, which may play a bigger role in influencing the lag behaviours for longer droughts (Li et al., 2020a; Yang et al., 2017), are most probably the main reasons. As the drought durations increase, physical connections including the extent and response times between precipitation and runoff become complex and nonlinear. For longer timescales, different drought resistance of catchments and the varying rate and timing of the groundwater and baseflow contributions can also play a big part in how soon after meteorological droughts hydrological droughts are experienced and how quickly the latter recovers after the former is ended (Guo et al., 2020; Kao & Govindaraju, 2010). This could be an area of investigation for subsequent research.

The drought recovery lag was much larger (median = 7 months, range 2 to 29 months) in the winter precipitation zone in the south-eastern Australian region which was most affected by the Millennium Drought. This concurs well with Peterson et al. (2021) who found that about a third of the catchments in this region did not return to the pre-drought condition even seven years after the Millennium Drought. These long-term changes are attributed to increased transpiration, suggesting that catchments may have finite resilience thus hydrological droughts may continue long after meteorological droughts have ended. We found that depending on the drought criteria, drought timescales affect the propagation and recovery lags differently. If the cessation of drought is defined as catchments returning to the predrought condition, i.e. equivalent to SSI < 0, the lag can be much larger than the maximum 29 months recovery lag found for HD using SSI <-0.5 criterion. For droughts of longer timescales, we showed that the propagation and recovery depend on the combination of SPI, SSI or SSMI in defining the onset and recovery criteria. For different MD onset criteria, lagtimes can vary for HD or AD even if the onset criteria for HD or AD are the same. This is because an incidence of severe HD in response to a moderate MD onset criterion can take longer than the incidence of a moderate HD. As noted earlier, for droughts of smaller timescales the lags are mostly independent of drought criteria therefore these effects are not pronounced at these timescales. As our research showed for different precipitation zones of Australia, Apurv & Cai (2020) found that spatial patterns of hydrological drought coincided with the climatic patterns in the contiguous USA and that the location and seasonality of precipitation have a role in drought propagation. Bachmair et al. (2015) also found connections between qualitative drought impact and hydroclimatic drought indicators were time-variant and region-specific.

We note that the lag between different drought types has been studied using the correlation and lag correlation. These approaches, however, can result in unexpected results due to reasons such as (i) the use of whole time series for correlation that also includes the non-drought positive index values (ii) correlation between two variables does not necessarily guarantee causality (iii) correlation analysis can be affected considerably by extremely high negative values in the standardised indices time series (e.g. Haslinger et al., 2014; Lorenzo-Lacruz et al. 2013; Peña-Gallardo et al., 2019). This is unlike the investigation of individual events, based on the one-to-one relationship exploring cause-and-effect reasoning as we have done in this research ensuring consistent accounting of each event.

As there are no universal definitions of drought (Agnew, 2000; Hao & Singh, 2015) and all the standardised hydroclimatic drought indices only indicate the occurrence of above- or below-average conditions rather than the absolute indication of dry or wet conditions. For example, regions with higher precipitations despite having the same negative SPI values, can still be much wetter than regions with lower precipitations (Paulo et al., 2016). Therefore, findings based on the SPI and other drought severity indices may not be uniformly helpful in all circumstances. Consequently, this research uses a range of drought criteria based on the value of indices to test the lagtimes for droughts of different severities. We argue that drought propagation needs to be studied in conjunction with a precise definition of drought as they have a big influence on the findings related to propagation and recovery lags.

Finally, we found the best-fitted probability distributions for annual total precipitation, streamflow and annual mean soil moisture content follow a mixture of gamma, lognormal, normal and Weibull distributions across Australia. Globally the existence of a range of distributions has also been reported by authors including for the USA and Canada (Guttman, 1999; Markovic, 1965); Europe (Lloyd-Hughes & Saunders, 2002); Japan (Yue & Hashino, 2007); Brazil (Blain, 2011); Sudan (Mohamed & Ibrahim, 2015); China (Li et al., 2020b; Wu et al., 2021) and Italy (Moccia et al., 2022) questioning the usual approach of estimating the standardised indices based on gamma distribution. Furthermore, Laimighofer & Laaha, (2022) found that choice of distribution was one of the main sources of uncertainty in estimating SPI leading to substantial errors in drought detection and classification. Therefore, these highlight the need for examining all possible distribution functions for calculating drought indices, as done in our study, rather than assuming a single default distribution (e.g. Edwards & McKee, 1997; Keyantash & NCAR Staff, 2018; Kirono et al., 2020; Paulo & Pereira, 2006; and references therein).

5 Conclusions

Understanding of linkages between different drought types is crucial to enhancing community resilience and planning for future climate changes. Despite Australia's vulnerability to severe droughts, lagtimes of propagation (and recovery) from one drought type to the other across its large hydroclimatic regions are not well understood. Therefore, we investigated propagation and recovery lags between meteorological and hydrological and between meteorological agricultural droughts for a combination of onset and cessation criteria in 407 catchments within six major precipitation zones across Australia using standardised drought indices. We found that for all drought types, the propagation and recovery lagtimes depend on the drought timescales and drought criteria. For droughts of smaller timescales, the propagation and recovery lags have strong and statistically significant relationships with recovery lag consistently greater than propagation time. However, as the drought timescale increases, the relationships weaken and become less clear most likely due to other drivers, such as regional groundwater, that affect the catchment's long-term response to precipitation. Notably, recovery lagtimes are longer for the high-yielding catchments in the uniform, winter and winter-dominated precipitation regions in eastern Australia compared to the other regions.

Finally, a range of probability distributions was fitted to raw hydroclimatic data to calculate the drought indices which revealed that gamma and lognormal are the two best-fitted distributions for annual total precipitation data while the gamma distribution fitted best to the annual total streamflow. The lognormal and normal distributions fitted best for the annual mean soil moisture data. These highlight the need for examining all possible distribution function for calculating drought indices.

Acknowledgments

This study was supported by CSIRO Environment - Chinese Academy of Sciences - Institute of Geographic Sciences and Natural Resources Research (IGSNRR) collaborative research fund. There are no real or perceived financial conflicts of interest for any author.

Data Availability Statement

All streamflow and precipitation data for the Australian Bureau of Meteorology's hydrologic reference stations are available from http://www.bom.gov.au/water/hrs/. The soil moisture data was obtained from ESA Climate Office https://climate.esa.int/en/projects/soil-moisture/. The codes are available upon request.

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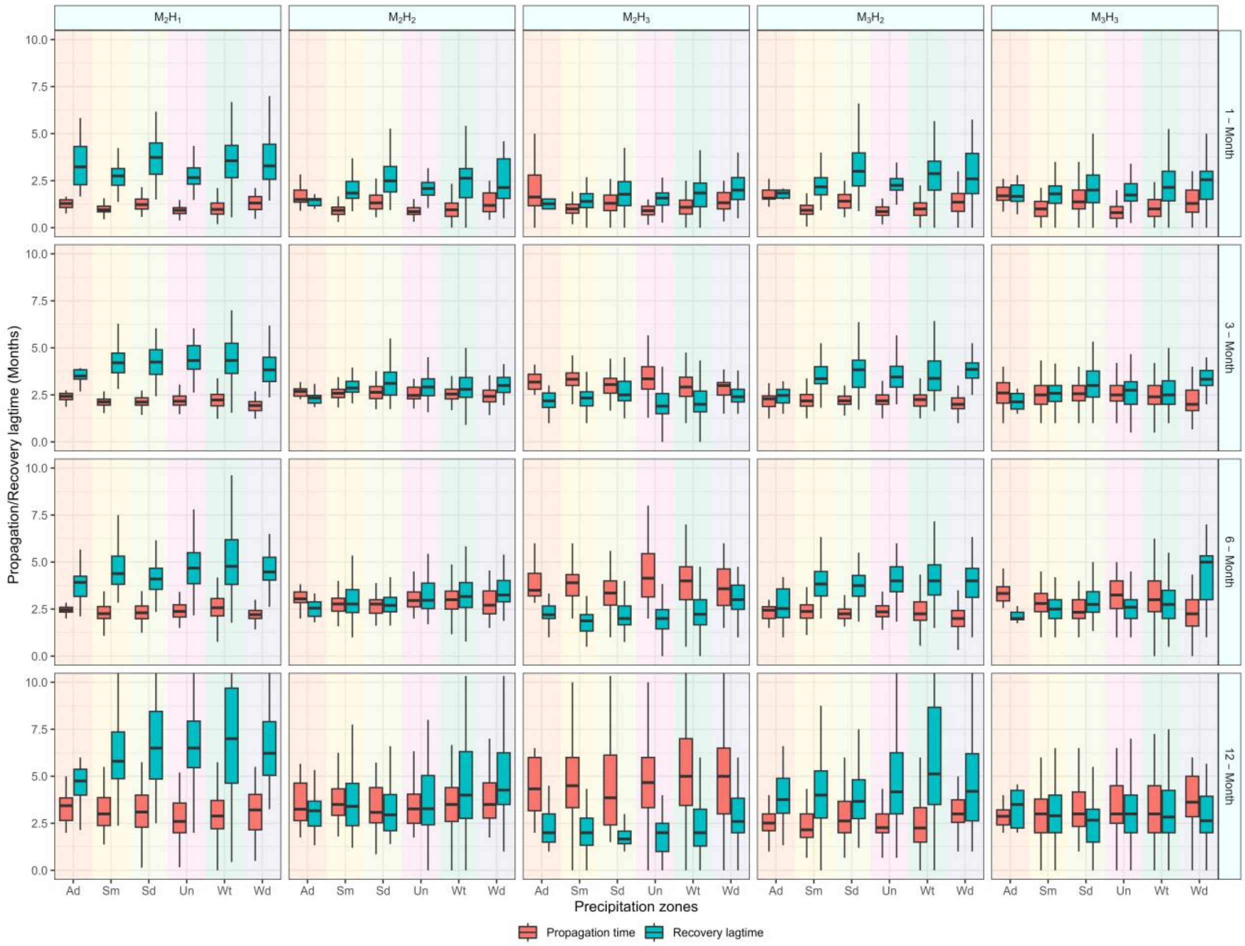
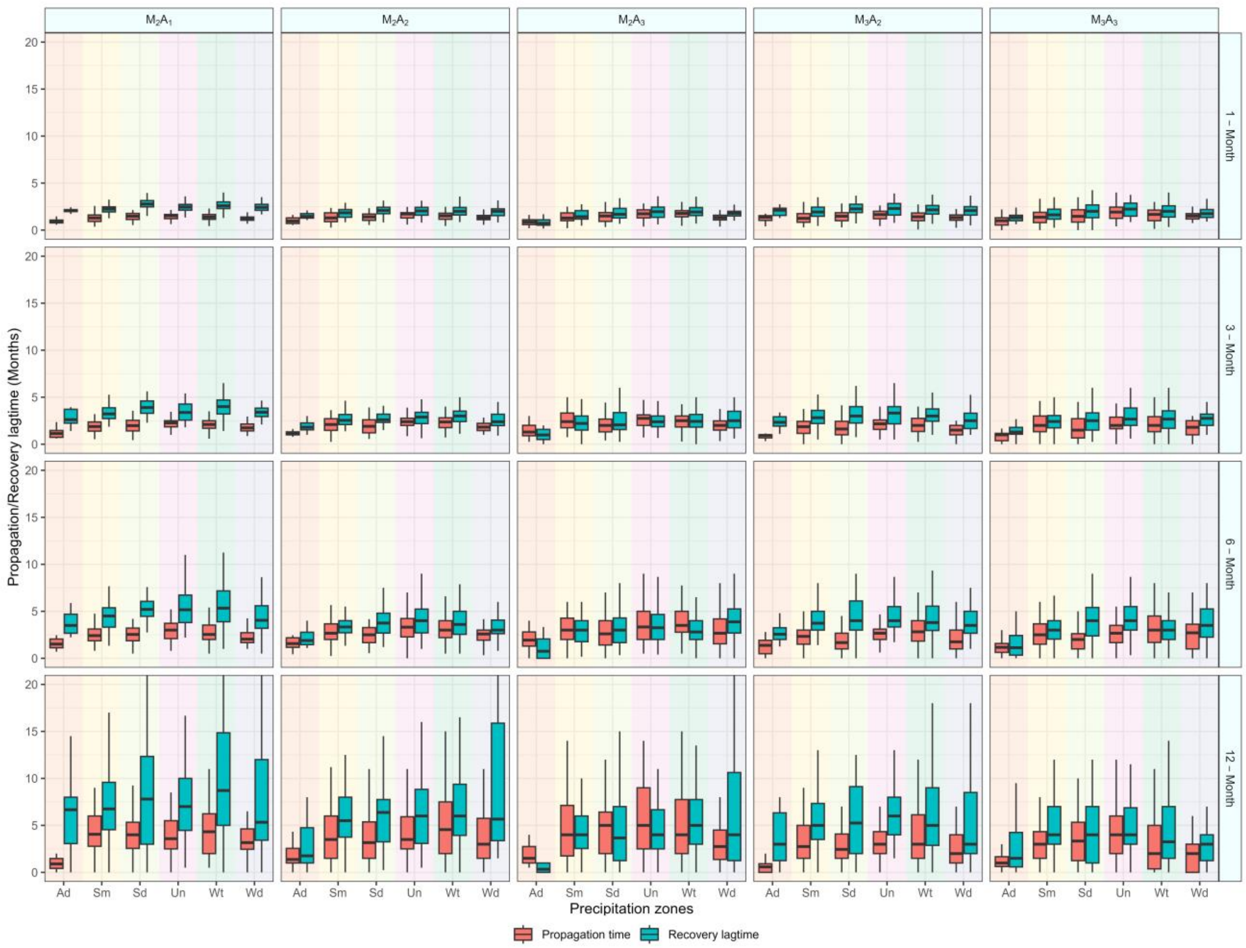
Supplementary Figures



Supplementary Figure 1: Distribution of propagation time and recovery lagtime (m) of hydrological droughts in each precipitation zone for different drought criteria and timescales as labelled in the panels.



Supplementary Figure 2 Distribution of propagation time and recovery lagtime (m) of agricultural droughts in each precipitation zone for different drought criteria and timescales as labelled in the panels.

Supplementary Tables

Supplementary Table S1 Coefficient of determination (r^2) showing strength of correlation between propagation and recovery lags for droughts of different durations and criteria. Numbers in bold show statistically significant correlation at 0.05 level while the numbers in italics depict negative correlation.

	Arid	Summer	Summer dominant	Uniform	Winter	Winter dominant
Drought Criteria			*1 Month*			
M_2H_1	**0.53**	**0.23**	**0.59**	**0.32**	**0.41**	**0.40**
M_2H_2	**0.75**	**0.43**	**0.45**	**0.29**	**0.29**	**0.40**
M_2H_3	**0.83**	**0.27**	**0.46**	**0.30**	**0.24**	**0.37**
M_3H_2	**0.57**	**0.24**	**0.46**	**0.31**	**0.19**	**0.52**
M_3H_3	**0.98**	**0.39**	**0.62**	**0.43**	**0.13**	**0.33**
	3 Months					
M_2H_1	***0.34***	**0.09**	**0.11**	**0.13**	**0.093**	0.017
M_2H_2	0.21	0.036	**0.23**	0.026	**0.049**	0.00099
M_2H_3	**0.62**	**0.061**	**0.16**	**0.086**	0.019	***0.14***
M_3H_2	**0.47**	0.0055	**0.2**	0.0033	0.028	0.04
M_3H_3	**0.5**	**0.12**	**0.12**	**0.21**	**0.074**	***0.11***
	6 Months					
M_2H_1	*0.12*	0.033	**0.077**	**0.059**	**0.033**	0.0063
M_2H_2	0.063	0.046	0.016	*0.0063*	**0.052**	0.012
M_2H_3	0.21	*0.00054*	0.0064	***0.068***	*0.003*	*0.054*
M_3H_2	0.17	0.016	**0.069**	0.00079	*0.002*	0.0097
M_3H_3	0.14	0.023	**0.069**	*0.036*	*0.0016*	*0.011*
	12 Months					
M_2H_1	0.046	0.00063	*0.00032*	**0.073**	*0.0012*	0.053
M_2H_2	*0.024*	*0.0057*	0.01	*0.023*	0.0017	0.019
M_2H_3	*0.29*	*0.01*	**0.084**	5.00E-04	***0.093***	*0.051*
M_3H_2	0.0018	***0.076***	0.002	*0.023*	***0.031***	*0.0033*
M_3H_3	*0.022*	*0.021*	0.0088	0.012	*0.00092*	0.014

Suplementary Table S2: Coefficient of determination (r^2) showing strength of correlation between propagation and recovery lags for droughts of different durations and criteria. Numbers in bold show statistically significant correlation at 0.05 level while the numbers in italics depict negative correlation.

	Arid	Summer	Summer dominant	Uniform	Winter	Winter dominant
Drought Criteria			*1 Month*			
M_2A_1	0.06	**0.58**	**0.13**	**0.52**	**0.45**	**0.39**
M_2A_2	**0.54**	**0.75**	**0.41**	**0.67**	**0.72**	**0.59**
M_2A_3	**0.47**	**0.77**	**0.71**	**0.73**	**0.58**	**0.53**
M_3A_2	**0.63**	**0.60**	**0.58**	**0.54**	**0.59**	**0.61**
M_3A_3	**0.75**	**0.70**	**0.71**	**0.73**	**0.66**	**0.54**
	3 Months					
M_2A_1	**0.39**	**0.12**	**0.09**	**0.35**	**0.09**	**0.21**
M_2A_2	**0.28**	**0.23**	**0.37**	**0.34**	**0.34**	**0.32**
M_2A_3	0.11	**0.36**	**0.32**	**0.33**	**0.12**	**0.11**
M_3A_2	**0.36**	**0.22**	**0.26**	**0.27**	**0.21**	**0.34**
M_3A_3	**0.35**	**0.41**	**0.33**	**0.27**	**0.18**	**0.35**
	6 Months					
M_2A_1	0.13	**0.17**	**0.41**	**0.14**	**0.16**	**0.15**
M_2A_2	**0.28**	**0.21**	**0.39**	**0.13**	**0.12**	**0.21**
M_2A_3	0.16	**0.10**	**0.51**	**0.07**	**0.05**	**0.25**
M_3A_2	0.18	**0.13**	**0.18**	0.01	**0.08**	0.06
M_3A_3	**0.72**	**0.11**	**0.19**	0.01	**0.05**	**0.19**
	12 Months					
M_2A_1	***0.27***	*0.00*	0.03	0.00	**0.04**	0.01
M_2A_2	0.00	0.00	*0.00*	*0.01*	0.02	*0.04*
M_2A_3	*0.04*	0.01	*0.06*	***0.13***	0.01	0.07
M_3A_2	0.20	0.01	0.00	*0.01*	0.02	**0.17**
M_3A_3	0.22	0.03	0.09	*0.02*	0.05	0.10