An Object-based Climatology of Precipitation Systems in Sydney, Australia

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An object-based climatology of precipitation systems in Sydney, Australia

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Abstract

The climate is warming and this is changing some aspects of storms, but we have relatively little knowledge of storm characteristics beyond intensity, which limits our understanding of storms overall. In this study, we apply a cell-tracking algorithm to 20 years of radar data at a mid-latitude coastal-site (Sydney, Australia), to establish a regional precipitation system climatology. The results show that extreme storms in terms of translation-speed, size and rainfall intensity usually occur in the warm season, and are slower and more intense over land between ~10am and ~8pm (AEST), peaking in the afternoon. Precipitation systems are more frequent in the cold season and often initiate over the ocean and move northward, leading to precipitation mostly over the ocean. Using clustering algorithms, we have found five precipitation system types with distinct properties, occurring throughout the year but peaking in different seasons. While overall rainfall statistics don't show any link to climate modes, links do appear for some system types using a multivariate approach. This climatology for a variety of precipitation system characteristics will allow future study of any changes in these characteristics due to climate change.

1. Introduction

Heavy rainfall is a significant threat to life and property in many parts of the world, especially when it contributes to flash floods (Johnson et al. 2016; Allen and Allen 2016). Many studies have shown the potential for climate change to impact rainfall intensity, but how it will affect other storm characteristics (size, translation speed, orientation, etc.) remains largely unexplored. The first step towards exploring the potential future changes is to establish an observed baseline for a wide variety of storm characteristics.

Climatological studies can help us to better understand rainfall characteristics, their local/remote drivers and their seasonal/diurnal variations. Many studies have used coarse-resolution gridded datasets (e.g., global climate models, reanalysis data) to perform climatological studies globally and over specific regions; however, the coarse-resolution of these datasets are unable to properly capture small-scale processes which can have important contributions to water availability and natural disasters like flash floods (Dowdy 2020). Although studying the non-severe small-scale precipitation systems is not feasible using these datasets, previous research has employed these products to establish a thunderstorm climatology based on the concept of favourable conditions for thunderstorms. These conditions usually include a combination of convective available potential energy (CAPE) and vertical wind shear in a region (Ahmed et al. 2019; Brooks et al. 2003; Taszarek et al. 2020; Allen et al. 2011; Groenemeijer et al. 2017). By employing this environmental approach, Allen and Karoly (2014) presented a severe thunderstorm climatology over Australia during 2003–2010, using the ECMWF Interim Re-Analysis (ERA-Interim) (Dee et al. 2011) and reported observation data. They showed that these types of storms are more frequent in December during the afternoon, consistent with the diurnal cycle of surface temperature and the maximum availability of heating. A limitation to this approach is that the environmentally favorable conditions do not necessarily lead to a thunderstorm, causing an overestimation of the thunderstorm frequency. In addition, most of the studies focused only on thunderstorm frequency. Although information on other storm characteristics can be provided based on environmental information, including severe winds, rainfall, hail and storm intensity (Dowdy 2020; Brown and Dowdy 2021), environmental approach is unable to provide more detailed information on other quantitative characteristics such as storm size, translation speed, direction, etc. (Allen and Karoly 2014).

Using coarse-resolution datasets, previous authors have tried to investigate the effect of natural climate variability (e.g., El Niño–Southern Oscillation (ENSO), the Indian Ocean Dipole (IOD)) and Southern Annular Mode (SAM) on the rainfall over Australia. Using an atmospheric general circulation model, Ashok et al. (2003) showed that IOD has significant negative partial correlations with rainfall over the western and southern regions of Australia. Dowdy et al. (2020) employed ERA-Interim data along with lightning and rainfall observations to examine the influence of large-scale drivers such as the ENSO, IOD and SAM on thunderstorm activities over Australia, finding no strong relations between them, consistent with findings of Allen and Karoly (2014). In another reanalysis-based study, Hauser et al. (2020) investigated the winter-spring

rainfall variability in southeastern Australia (SEA) during El Niño events by quantifying the contribution of clustered mid-latitude weather systems to monthly precipitation anomalies. The authors found that the cluster with below-average rainfall is more frequent compared to the other clusters during El Niño, which confirmed the general suppression of SEA rainfall during these events. Since precipitation in some regions can be correlated with more than one large-scale driver, and indices are often correlated with each other, the interconnected nature of precipitation dependence suggests the need for a multivariate rather than bivariate approach to this problem. Maher and Sherwood (2014) applied a multivariate approach to Australian precipitation to disentangle the multiple sources of large-scale variability using the ERA-Interim and Australian Water Availability Project (Jones et al. 2009) datasets, and they showed that ENSO, blocking, and the intensity and position of the ridge are driving wintertime precipitation in Australia, with a minor role played by the jet intensity and the IOD. All of these studies investigated the effects of natural climate variability on rainfall over large-scale regions and uncertainties remain in local areas such as Sydney. In addition, the focus of these studies was mainly on intensity and frequency, and did not consider relationships between other characteristics of precipitation systems (i.e., size, shape, translation speed, etc.) and climate modes.

Another approach to investigate thunderstorms is measuring the occurrence of lightning using satellite instruments such as the Optical Transient Detector (OTD) and/or the Lightning Imaging Sensor (LIS) (Boccippio et al. 2002; Christian et al. 2003). Dowdy and Kuleshov (2014) produced a climatological map of lightning ground flash density over Australia, which details the seasonal variability of the lightning ground flash densities over land and ocean. They found that during the cooler months, a maximum in lightning activity occurs over the ocean to the east of the continent. Earlier studies by Kuleshov et al. (2001; 2012) had found that the second-highest thunderstorm frequency occurs in the southeast part of Australia along the coastline, most often from spring to early autumn. Similar research has been conducted globally for regions such as the United States and Europe (Taszarek et al. 2020), Brazil (Pinto et al. 2013) and middle-east (Shwehdi 2005). Although this approach provides valuable information regarding thunderstorms, it only reveals precipitation systems that produce lightning. Additionally, it provides limited information regarding storm frequency and intensity (Dowdy and Mills 2012; Dowdy 2020), and other information like storm size, shape, which are poorly or unrelated to lightning flash rates (Walsh et al. 2016).

Point-based datasets like rain gauges and reports of hail, tornado and wind gusts are other means of studying precipitation systems used in many studies (Bhardwaj and Singh 2018; Enno et al. 2013; Saha and Quadir 2016; Pinto et al. 2013; Groenemeijer et al. 2017; Kelly et al. 1985; Doswell et al. 2005). The databases of reported tornadoes, hailstorms, and wind gusts in some countries like Australia have a long-term record (Bureau of Meteorology 2021), which can provide valuable information for severe thunderstorm studies. Using these datasets over Australia, some researchers have found that severe thunderstorms are most prevalent between October and April (Niall and Walsh 2005; Schuster et al. 2005; Davis and Walsh 2008) with a peak between 3 and 7 pm (Griffiths et al. 1993; Schuster et al. 2005), consistent with the findings of Allen and Karoly

(2014) using environmental approach and ERA-Interim reanalysis data. Higher frequency of heavy rain events over Australia in summer was also reported by Dare and Davidson (2015), using a high resolution gridded daily rain gauge data. Some efforts have also been made to employ point-based datasets to investigate relationships between ENSO and storm events, globally (Cook and Schaefer 2008; Cook et al. 2017; Lee et al. 2016, 2013; Lepore et al. 2017) and over Australia (Chung and Power 2017; Risbey et al. 2009a,b; Murphy and Timbal 2008; Nicholls et al. 1996; McBride and Nicholls 1983; Allan et al. 1996; Schepen et al. 2012; Min et al. 2013; King et al. 2014; Ashcroft et al. 2019). Based on these studies, winter-spring rainfall is usually reduced during El Niño and enhanced during La Niña over the eastern and southeastern parts of Australia. However, the relationships are stronger inland and weak or absent in coastal regions. Although point-based data have been widely used in climatological studies, their availability is highly influenced by the local population density (Allen 2018). In addition, climatological studies using reported data are mainly focused on severe storms rather than non-severe ones. Although gauge networks have the potential to provide information regarding both severe and non-severe precipitation systems, the sparse networks often fail to observe the maximum intensity (Ayat et al. 2018) or even miss precipitation systems altogether (Lengfeld et al., 2020).

The limitations of these approaches have led to the application of remotely-sensed datasets, which can observe the precipitation systems with high resolution in space and time. Satellite precipitation products have been widely used in rainfall climatological studies across the world (Kidd 2001; Atiah et al. 2020; Chua et al. 2020; Morin et al. 2020). (Kidd 2001; Atiah et al. 2020; Morin et al. 2020) Some studies (Cecil and Blankenship 2012; Ni et al. 2017) have applied a satellite-based approach using passive and active microwave sensors to estimate the global climatology of hail storms. However, images from these sensors are available only for a few overpasses per day (Ayat et al. 2021a), which may result in biasing the results depending on the diurnal cycle of convection in the respective regions (Punge and Kunz 2016). In addition, passive microwave products are capturing the upper part of the storms in which there might be more hail particles that melt/evaporate at lower altitudes, leading to false estimation of hail on the ground surface (Ayat et al. 2021b).

High spatio-temporal resolution radar rainfall estimates offer great potential to study a wide range of precipitation systems that appear in their coverage areas, particularly over the regions in which gauge observations are usually sparse or unevenly distributed (Ghaemi et al. 2017; Ayat et al. 2018; Moazami et al. 2014). Radar records in many parts of the globe are temporally limited to just over a decade (Allen 2018). However, this time frame is long enough to conduct climatological studies. Previous researchers have employed these datasets to study the climatology of precipitation systems over specific regions such as the United States (Ghebreyesus and Sharif 2020; Kuo and Orville 1973; Croft and Shulman 1989; Falconer 1984), Europe (Kaltenboeck and Steinheimer 2015; Kreklow et al. 2020; Weckwerth et al. 2011; Overeem et al. 2009; Bližňák et al. 2018; Fairman Jr et al. 2015) and Asia (Chen et al. 2012).

Hail particles are readily detected by conventional weather radars due to strong scatter produced by their comparatively larger surface area, or via their different shape compared to oblate

rain droplets, which produces distinct differential reflectivity values for dual-polarization radars. Using these properties, a few radar-based hail products have been produced and employed to study the climatology of hailstorms over different regions. For instance, Warren et. al (2020) studied the hail climatology in multiple cities in Australia (including the Sydney region) using a radar-based hail product (Maximum Expected Size of Hail; MESH; (Witt et al. 1998)), and found that, on average, damaging hail storms over Sydney occur 32 days per year with a peak during the warm season (November-March), consistent with the findings of similar study by Dowdy et al. (2020). Similar radar-based studies have been conducted over other parts of the globe like Europe (Junghänel et al. 2016; Nisi et al. 2016; Fluck et al. 2021; Lukach et al. 2017; Saltikoff et al. 2010) and the United States (Cintineo et al. 2012; Murillo et al. 2021).

Most of the previous radar-based studies employed a pixel-based statistical approach which limits the storm properties to rainfall/hail frequency and intensity as a function of position. In order to overcome this limitation, a few studies have employed an object-based approach, where discrete storm objects are identified and characterized. For instance, Haberlie and Ashley (2019), Poujol et al. (2020) and Prein et al. (2017) applied object-based techniques to radar products to study the climatology of convective storms in the United States. In Australia, Soderholm et al. (2017) employed a cell-tracking algorithm over radar MESH product to study hail climatology in southeast Queensland. Hitchcock et al. (2021) also studied the characteristics of linear precipitation systems and their contributions in heavy rainfall over Melbourne by applying and object-based approach over a weather radar data near Melbourne. Similar efforts have been made in Germany (Thomassen et al. 2020), Italy (Sangiorgio and Barindelli 2020) and Spain (Rigo et al. 2010).

Although object-based techniques can provide more information on storm characteristics, the investigated storm properties in most of these studies were limited to storm number, area, and rainfall intensity, whereas other storm characteristics like storm translation speed, shape and aspect ratio, orientation, direction and volume could also be of interest. In addition, the object-based techniques employed in these studies are limited by the object split/merge issue, which is a common problem in object-tracking methods and can lead to calculating misleading storm properties (Muñoz et al. 2018). In many tracking algorithms, when a system merges to (or splits from) another system, it is considered as a separate system with its own properties. Handling split/merge events results in including independent small-scale objects (that are connected via split/merge) as a large object. Thus, we will have a better estimation of system frequency and area at each snapshot, which results in a better estimation of other area-dependent properties, such as mean system direction and velocity derived by area-weighted averaging of each property. In addition, considering multiple connected objects (via split/merge events) as a united object at each snapshot enables us to have a more realistic estimation of an object centroid at each snapshot, resulting in having a better estimation of system track and track-length, direction and lifetime, as well.

In this research, we employ the Method of Object-based Diagnostic Evaluation (MODE; (C. Davis et al. 2006)) Time Domain (MTD; Clark et al. 2014), which is modified by the authors

so as to handle splitting and merging of objects. We apply this technique to the Wollongong radar, located near Sydney, Australia, which has around 20 years of records, to establish an object-based climatology of precipitation in different seasons over the radar footprint areas (i.e., Greater Sydney, Illawarra and other land/ocean regions within 150 km of the radar). We group the main contributing storms with similar object-based characteristics using clustering algorithms, then investigate their relationships with different climate modes.

This study is presented in seven sections. Section 2 describes the Wollongong radar data and its characteristics. Section 3 introduces the object-based and clustering methods along with the statistics employed in this study. Section 4 describes the study area and section 5 presents the results of the object-based climatology over the study area. Section 6 discusses the results shown in the previous section, and finally, the summary of findings is presented in section 7.

2. Dataset

3.1 Radar Data

This study uses data from a Bureau of Meteorology operational S-band weather radar located near Wollongong, NSW (34.26° S, 150.88° E, 471 m altitude; (Soderholm et al. 2020)). The site experiences partial blocking up to 3 dB in the lowest scan (0.5° elevation) from the northwest to the southeast due to the significant terrain associated with the Great Dividing Range. The archive for this radar started in November 1996 and the site continues to operate as of 2021. However, the study period is limited to June 2018 in this study. Several hardware and configuration changes have taken place during the lifetime of the radar. Initially, the radar operated on a 10-minute volume cycle with 16-level reflectivity data (which is sampled at 16 discrete levels: 12.0, 23.0, 28.0, 31.0, 34.0, 37.0, 40.0, 43.0, 46.0, 49.0, 52.0, 55.0, 58.0, 61.0, and 64.0 dBZ). In December 1999 the number of reflectivity levels was increased to 64. Between October 2010 and January 2021, a major hardware upgrade delivered 160-level reflectivity data and a 6-minute volume cycle. One significant gap is present in the archive from 1/1/1998 to 15/12/1998.

To ensure the accuracy of reflectivity values across the entire dataset, an absolute calibration technique is applied using precipitation radar measurements from the Tropical Rainfall Measuring Mission (TRMM) and the Global Precipitation Measurement mission (GPM). Satellite overpasses with precipitation are compared with ground radar measurement using the volume matching technique described by Louf et al. (2019), providing a mean calibration value for every pass. Periods of stable calibration are identified (through manual inspection of the stable clutter time series and knowledge of radar inspection dates), and the mean absolute calibration value for these periods is applied as an offset to the ground radar data. Removal of non-meteorological echoes from reflectivity datasets is challenging. In addition to the ground clutter filtering performed by the signal processor, the technique described by Gabella et al. (2002) is applied using filters for echo continuity and minimum echo area. Unfortunately, this technique is not suitable for removing anomalous propagation which is commonly observed over Tasman Sea. However, we have conducted additional analyses to address this issue (described in section 3.2)

Reflectivity data are transformed to rain rates using a fitted Z-R relationship ($Z=A \times R^B$) derived from 9 years of hourly rain gauge data using the Camden Airport AWS (35.04° S, 150.69° E). Note that in the Z-R relationship, Z is the reflectivity (mm^6m^{-3}), R is precipitation intensity (mm/hr) and A and B are the constant coefficients that are dependent on the region and precipitation type. The A and B coefficients for this radar are 81 and 1.8 respectively. The maximum rain rate is limited to 100 mm/hr to limit contamination from hail. Volumetric rain rates are transformed into a Cartesian grid at a 0.5 km altitude using the Barnes weighting function and a 2.5 km constant radius of influence. The final grid has a horizontal resolution of 1 km and a domain size of 300 km by 300 km. However, observations are limited to within 150 km of the radar.

3.2 Challenges with anomalous propagation

Despite all the efforts made in removing non-meteorological echoes, the Wollongong radar site experiences significant anomalous propagation over the ocean within the eastern portion of its coverage. These echoes primarily occur during heat-wave conditions, where strong low-level vertical gradients of humidity and temperature create regions of super refraction for lower elevation scans. The resultant echoes have similar reflectivity gradients, size and shape to precipitation echoes, while also being non-stationary, limiting the effectiveness of any algorithms to remove non-meteorological echoes from reflectivity data (fig S9a; Online Resource 1). In order to reduce the effect of these clutter sources in precipitation estimates, we have opted for a two-step clutter removal process over the whole dataset: 1) Since these clutters often include pixels with low intensity, applying the 3 mm/hr threshold over the convolved data (to detect the storm objects; see section 5.1), effectively removed this clutter throughout the year (fig S9b; Online Resource 1) except some extremes in summer (fig S9d; Online Resource 1). 2) The days with extreme clutter were removed manually from the dataset using maximum daily reflectivity maps (see fig S8; Online Resource 1) such that the days with high values of maximum reflectivity over the ocean and low values over land were considered as a day with extreme clutter over the ocean.

3. Study area

The study area in this research is the radar coverage regions located up to 150 km from the Wollongong radar, which includes coastal regions of Greater Sydney and Illawarra in New South Wales. The climate of these regions is categorized as humid subtropical, based on the Köppen–Geiger classification (Kottek et al. 2006), and is significantly affected by the coastal position, with small interseasonal variations ranging from cool winters to warm and hot summers (Dare and Davidson 2015). The mean annual precipitation recorded at Observatory Hill (33.86° S, 151.20° E; in Greater Sydney) and Wollongong University (34.40° S, 150.88° E; in Illawarra) locations are 1213.4 mm and 1348.6 mm, respectively (Bureau of Meteorology 2013).

Several factors may impact the precipitation over these regions and its seasonality. Generally, precipitation peaks in the first half of the year and decreases in the second half (Dowdy

et al. 2015). In the summer, the easterly (or inland) trough is a major contributor to rainfall over these regions with a peak in the evening. Its impact can be enhanced by interacting with any upper-level troughs or cold fronts crossing over these regions. Frontal systems also bring rainfall to these regions throughout the year, but mostly in winter when the subtropical ridge moves northward over inland Australia (Bureau of Meteorology 2010). Another source of precipitation over these regions is cut-off lows, which can occur at any time of year but are most common during autumn and winter. These can be intense and last up to a week when formed as part of a blocking pair or east coast lows (ECL), in which case they are accompanied by long-lasting heavy rainfall and gusty winds (Bureau of Meteorology 2007). ECLs are among the most dangerous weather systems affecting the eastern coast, and are the reason for many major floods in this region (Callaghan and Power 2014; Dowdy et al. 2019), especially when they are concurrent with other phenomena such as fronts and thunderstorms (Dowdy and Catto 2017). Northwest cloud bands (stretching from northwest to southeast Australia) can also bring precipitation over these regions. They may interact with cold fronts and cut-off lows over southeastern Australia to produce very heavy rainfall over these regions (Reid et al. 2019). Several modes of variability are known to affect precipitation in Australia (Min et al. 2013; King et al. 2014), However, precipitation over the coastal zone, that includes our study area, has shown little relationship (Timbal and Hendon 2011; Pepler et al. 2014; Fita et al. 2017).

4.1. Method of Object-based Diagnostic Evaluation (MODE) Time Domain (MTD):

MODE is an algorithm that was developed at the Research Applications Laboratory, NCAR/Boulder, USA to extract the object-based precipitation properties from gridded datasets (Davis et al. 2009). (C. Davis et al. 2006; Davis et al. 2009)MTD is an extension for MODE to track the objects detected in a precipitation map by the MODE algorithm (Clark et al. 2014). Here we employed a modified version of MTD, proposed by Ayat et al. (2021b), that considers split/merge events during the lifetime of a precipitation system. In this method, the “objects” at each time step are the connected pixels higher than a specified threshold in the convolved precipitation map (smoothed by an $n \times n$ -pixel moving window across the map). Every object at each time-step has a unique label number unless it has overlap with another object at the previous time-step (each blob in figure 1c). In this case, it takes the label of the object at the previous time-step. If an object has overlap with two (or more) objects in the previous time step (merging) or two (or more) objects have overlaps with a object at the previous time step (splitting), the object/objects at the current timestep takes/take a new label. Based on these definitions, A “sequence of objects” is the connected objects in time that has a unique label number and doesn’t have split/merge events during its lifetime (connected blobs with the same colours and numbers in figure 1c). Finally, a “system” is a group of sequences that are connected via split/merge events (The whole diagram in figure 1c). Note that the area-overlapping approach in tracking objects has limitations in tracking fast-moving small-scale precipitation systems (see fig S18; Online Resources 1) in which the included objects may not have area overlaps in some snapshots (time-step). While this impacts a very small proportion of systems, all of the analyses related to the system properties and time-

dependent object properties in this study are carried out by excluding this type of system. However, object properties of these systems that are not time-dependent are still included. Existing gaps in the radar archive (fig. S6) are considered by allowing up to 30 minutes between two radar precipitation maps while still tracking objects. A gap longer than this results in new systems after the gap.

Figure 1b represents an example of running the modified MTD on Wollongong radar data during an event that occurred on 2018-10-4. The lines with different colors are showing the sequence tracks. In this event, land-originating systems had a southeastward direction and later were merged with the systems that had formed over the ocean. Using original MTD, the connected land/ocean-originating systems via split/merge events are considered as a system, and we can have access to only mean system properties and mean object properties at each snapshot. Consider two groups of objects in a system, one over the land and the other over the ocean, that are moving fast towards each other and will merge somewhere in between. Based on the original MTD approach, the centroid of the system at each snapshot is always a slow-moving point which has a short track between the land and ocean systems with a different direction than the member objects. This can be a good presentation of the mean system properties, but it is not presenting the details of the objects' properties within a system. In our approach, we can have access to the information of a system and its member objects at the same time such that at each snapshot the properties of all the objects in a system are accessible as a whole (by averaging) and separately.

In this research, we are studying the extracted characteristics related to “systems” and “objects” using the modified MTD method. We are not performing the analyses for the sequences as we found the results from the objects is similar to sequences. The selected threshold to filter the objects is 3 mm/hr in the convolved data smoothed by a 3×3-pixel moving window across the map. The object characteristics of interest in this study include: 1) area: the number of pixels in the object multiplied by the pixel area (here is 1 km²); 2) translation speed: the ratio of the distance between the volumetric centroid (average of the x and y coordinates of all pixels in the object weighted by the pixel value) of two connected objects in time to the temporal resolution of the dataset; 3) maximum intensity: the maximum precipitation rate within an object; 4) average intensity: the average precipitation rate of all cells within an object; 5) volume discharge: the integration of rain rate within an object; 6) aspect ratio: the ratio of the minor and major axis of the fitted ellipse over an object; 7) direction: the deviation angle from north of the line connecting the centroids of two consecutive objects in a sequence indicating the direction the object is travelling to, and finally, 8) orientation that is the deviation angle from north of the major axis of the fitted ellipse.

The studied system characteristics in this research include: 1) mean area: the average system snapshot areas in the system lifetime; 2) mean volume discharge: the average system snapshot volume discharge in the system lifetime; 3) mean average intensity: the average of precipitation rate in the system lifetime; 4) max average intensity: the maximum of system averaged intensity (calculated at each snapshot) in the system lifetime; 5) mean translation speed: the area-weighted average translation speed of the system snapshots in the system lifetime; 6)

mean translation direction: the area-weighted average direction of the system snapshots in the system lifetime; 7) root object count: The number of root objects in the system graph diagram (e.g. in figure 1 object numbers 1, 2 and 3 are the root objects in the system diagram) and 8) split/merge count: the number of split/merge events in the system lifetime. Note that since translation direction is a cyclic quantity (0-360°), first we convert translation direction and speed into u and v components, then we apply the area-weighted averaging process on these two parameters, and finally convert the results back to mean translation speed and mean translation direction. It should be also noted that a minimum of 5 km² for object area has also been considered in the analyses to exclude very small-scale objects that can be generated by clutters. This threshold also excludes the fast-moving small-scale objects (less than 5km²) that cannot be tracked due to the limitations of the area-overlapping approach in tracking these types of objects. Using area-weighting in calculating system properties increases the contribution of large-scale objects and provides a more representative presentation of system properties.

354
 355 Fig. 1 Panel (a) shows the location of the Wollongong radar, Camden Airport, Observatory
 356 Hill and Wollongong University station. Panel (b) shows the sequence tracks for systems that
 357 occurred on (2018-10-04; UTC). Panel (c) illustrates the diagram of a tracked system with
 358 split/merge events. Note that each blob represents an object at each system snapshot (time step)
 359 and each colour shows a sequence.

360 4.2. Clustering Analysis

361 The aim of this section is to find system clusters (types) with similar quantitative
 362 characteristics over the study area using both the Agglomerative clustering algorithm and the t-
 363 SNE technique.

4.2.1 t-Distributed Stochastic Neighbor Embedding (t-SNE)

t-SNE is a statistical technique to visualize high-dimensional data by projecting it on a two or three-dimensional map. Here is a brief overview of the main stages in this method: 1) It starts with constructing a probability distribution of similarities (here is defined by the Euclidean distance between objects) over pairs of events in high-dimensional data such that a similar pair of events have a higher value compared to the one that is less similar; then, 2) another probability distribution of similarities is defined over the points in the low-dimensional map, and finally, 3) the algorithm minimizes the divergence between two distributions using Kullback–Leibler divergence parameter (KL divergence) between the two distributions with respect to the locations of the points in the map. Note that the KL divergence parameter is a measure of how one probability distribution differs from another using a gradient descent method. For more details, please refer to the original research paper by Maaten and Hinton (2008).

4.2.2 Agglomerative clustering

The agglomerative technique is one of the common types of hierarchical clustering in grouping data based on their similarity. This technique works in a “bottom-up” manner by treating each object as a separate cluster in the beginning. At each step, the two clusters with the most similarity are merged into a bigger cluster and this process continues until all objects are merged into one single big cluster (Subasi 2020). Here we have used the t-SNE algorithm to project our n-dimensional data on a two-dimension map (see fig 9a) and increase the divergence of potential clusters. Then, the agglomerative technique has been employed over the projected data to find the clusters. Similar process has been repeated by applying KMeans clustering algorithm (see fig S7; Online Resource 1). However, based on the density map, the cluster borders have been better recognized by the agglomerative technique.

In order to find independent properties as the input for the clustering algorithm, the correlations between all pairs of the object properties have been calculated and the pairs with correlation higher than 0.5 are considered as dependent variables and haven't been used together as the input in the clustering algorithm. Note that all input data are normalized (ranging from 0-1) by dividing each input system property by its standard deviation after subtracting its mean.

One of the problems with hierarchical clustering is that it doesn't give information regarding the number of clusters, or where to stop the merging process in the algorithm. In order to overcome this limitation, we have employed the Calinski Harabasz index (CHI) to define the number of clusters which is the optimum value of CHI. CHI is the ratio of between-cluster variance (VAR_B) to within-cluster variance (VAR_W). This parameter is calculated according to equations 1-3. In these equations, N is the population of the data, K denotes the number of clusters, and Z_k and z refer to the centroid of cluster k and the entire data, respectively. In the second and third equations, n_k is the population of cluster k and x_i denotes each member of that cluster (Li et al. 2018). Note that in equations 2 and 3, Z_k and Z are vector variables which are the two components of the projected system properties here.

$$CHI = \frac{VAR_B}{VAR_W} \times \frac{N-K}{K-1} \quad (1)$$

$$VAR_B = \sum_{k=1}^N n_k |z_k - z|^2 \quad (2)$$

$$VAR_W = \sum_{k=1}^K \sum_{i=1}^{n_k} n_k |x_i - z_k|^2 \quad (3)$$

4.3. Statistics

Here we employed the non-parametric Kendall's Tau rank correlation coefficient (tau) to investigate the strength of relationships between variables. This value is derived from the equation 4. In this equation, N_C is the number of matched pairs and N_D is the number of mismatched pairs of the two variables and n is the size of the variables (Wilks 2011).

$$tau = \frac{N_C - N_D}{n(n-1)/2} \quad (4)$$

To determine the significance of the difference between the two data distributions, the nonparametric statistical Kolmogorov-Smirnov test (KS-test) has been employed. This technique is a non-parametric test which doesn't need the input data distributions to be normal. The null hypothesis in this test is that both samples come from a population with the same distribution. This null hypothesis is rejected at the level of α if:

$$D_S > C(\alpha) \sqrt{\frac{n+m}{n \times m}} \quad (5)$$

$$D_S = \sup_x |F_n(x_1) - F_m(x_2)| \quad (6)$$

$$C_\alpha = \sqrt{-\ln\left(\frac{\alpha}{2}\right) \times \frac{1}{2}} \quad (7)$$

Where D_S denotes the KS statistic and n, m are the sizes of the two datasets. F_n and F_m refer to empirical distribution functions for both variables, and $\sup$ is the supremum function. Note that the supremum function of a subset S of a set K is the least element in K that is greater than or equal to all elements of S (Wilks 2011).

In order to model the relationship between two or more variables, in this research, we have employed the Ordinary least squares (OLS) method which is derived from equations 8-10. In these equations, n is the number of observations, p is the number of independent variables, y is the $n \times 1$ matrix of the dependent parameter, X is the $n \times p$ matrix of independent variables. Suppose b is a "candidate" value for the parameter β which is the $n \times 1$ matrix of coefficients for independent variables.

$$y = \beta X \quad (8)$$

$$\beta = \operatorname{argmin}_{b \in R^p} S(b) \quad (9)$$

$$S(b) = (y - Xb)^T (y - Xb) \quad (10)$$

An effort has been made in this study to investigate the relationships between climate modes (i.e., ENSO, IOD and SAM) and system properties in each cluster (derived from the previous section). Since precipitation can be correlated with more than one index, and the indices are often correlated with each other (Maher and Sherwood 2014; Taschetto et al. 2011; Mekanik et al. 2013; Mekanik and Imteaz 2012), we have utilized a multivariate approach rather than a

bivariate approach to consider the dependency of the climate modes on each other. The indices selected to quantify the mentioned climate modes are Niño 3.4, dipole mode index (DMI) and Antarctic Oscillation (AAO), respectively. Niño 3.4 is the average sea surface temperature anomaly over the Pacific Ocean in the region bounded by 5°N to 5°S, from 170°W to 120°W (Rayner et al. 2003). DMI describes the difference in SST anomalies between the tropical western Indian Ocean (10°S-10°N, 50°E-70°E) and the tropical southeastern Indian Ocean (10°S-0°, 90°E-110°E) (Saji et al. 1999). AAO is defined as the leading principal component (PC) of 850 hPa geopotential height anomalies south of 20°S (Thompson and Wallace 2000). Equation 11 is the model representing the relationship between the three selected indices and each object-based system properties (in each cluster) for every month using a multiple linear analysis to consider the dependency of the selected indices and include the annual variations. In this equation, C_0 is the Month constant and C_1 , C_2 , C_3 are Niño 3.4, DMI and AAO coefficients, respectively. Note that in this equation, each object-based property at every timestep is matched with its monthly climate indices. In addition, in order to derive the partial correlation between every index and storm property, all the coefficients have been normalized according to equation 12. In this equation, σ is the standard deviation, “index coefficient” refers to any calculated coefficient from equation 11 and “index normalized coefficient” is the partial correlation between every index and system property. Note that the monthly time series of Niño 3.4, DMI and AAO from NOAA, which refer to ENSO, IOD and SAM are accessible from the NOAA Physical Sciences Laboratory (information available online at <https://psl.noaa.gov/data/climateindices/list/>)

$$Storm \propto = C_0 + C_1 \times Ni\tilde{no}3.4 + C_2 \times IOD + C_3 \times SAM \quad (11)$$

$$index \text{ normalized coefficient} = \frac{index \text{ coefficient} \times \sigma (index \text{ values at each month})}{\sigma (storm \text{ properties at each month})} \quad (12)$$

4. Results

The object-based system properties are compared in different seasons in section 5.1 followed by the detailed analyses of the systems originating on land and ocean. Then, the diurnal cycles of system and object properties are analyzed in section 5.2. Finally, in section 5.3 the main contributing systems with similar object-based properties are clustered, and the effect of climate variability (i.e., ENSO, IOD and SAM) on these clusters is investigated. Note that by applying the object-based technique over the study period, 1,218,787 objects and 35,445 systems have been identified. From the detected objects, 252,636, 277,406, 371,389 and 317,356 objects are detected in spring (SON), summer (DJF), autumn (MAM) and winter (JJA), respectively. The corresponding numbers for systems are 8233, 8091, 10080, 9041. Note that many figures in this section use abbreviations in titles, axis labels, etc. due to lack of space. To better understand their reference please refer to table S8 in the supplemental materials.

5.1. Seasonal analyses of system/object properties

Fig. 2 System properties' distributions for different seasons. Note that the bins in the x-axis are equally spaced in the logarithmic scale except panels "e-h". Panel "c" is also presented in polar coordinates. Purple, red, orange and blue lines refer to spring, summer, autumn and winter, respectively. The y-axis in cartesian plots and radius in polar plots show the normalized frequency ranging from 0-100. Note that all the angles shown in panels "c" are azimuthal angles.

Fig. 3 The same as figure 2 but for object properties.

Figure 2 and 3 represents the PDFs of the system and object properties, respectively, in different seasons. According to these figures, here we define the “average”, “typical” and “extreme” values of a property as the mean, mode and the average of the top 5%, respectively. Figure 2 and table S1 show that systems in summer and spring tend to move towards the east-southeast (fig 2c), and are around 30%, 45% larger in average size (fig 2g) and volume (fig 2h), respectively, compared to the autumn and winter systems which usually move northward.

Comparing the mode of PDFs of both mean and maximum average rainfall intensity of systems (fig 2e,2f) shows that typical systems in autumn are around 15% and 30% more intense, respectively, than the other seasons. However, in terms of extremes, rain intensity is higher the warmer the season, since systems with maximum average intensity above 40 mm/hr (top 10% of systems in maximum intensity) during spring, summer, autumn and winter have occurred 1194, 1662, 1182 and 441 times, respectively, within the study timeframe. Note that systems in summer tend to include more root contributing objects and split/merge events than other seasons (see table S1), and the differences are clearer in the top 10% (fig 2a, 2b).

According to figure 3, objects in different seasons have almost the same characteristics as systems described above. However, the differences between seasons are smaller, and they look similar in some properties, such as area. Note that in autumn objects and systems tend to move slower (between ~10-20%; fig 3f, 2e) and look slightly more symmetric (fig 3h) than in other seasons. In addition, typical summertime objects are mostly oriented around 42° from north while in autumn and spring the object orientation angles change to around 66° and in winter objects are mostly oriented west-east (~100°; fig 3g).

Fig. 4 PDFs of system properties for systems originating on land (solid lines) and ocean (dashed lines). All differences between land and ocean distributions are statistically significant based on the Kolmogorov–Smirnov test. NL indicates the number of systems originating on land and NO refers to the system originating on the ocean.

Precipitation systems may have different characteristics based on their origination source and their locations on land or ocean, due to the distinct air mass properties and environmental characteristics that exist over these two surface types. Here, we have compared the average and extreme systems properties originating on land (L-systems) vs. ocean (O-systems) in different seasons by comparing their PDFs shown in figure 4. The results show that systems in spring and summer mostly initiate over land (~55%) and ~14% of total systems hit the ocean. However, in autumn and winter systems often originate over the Tasman Sea (~60%) and less than 10

% (of total systems) reach land (see table S7). L-systems, on average, are at least ~50% larger (fig 4a-d) and ~10% move faster (fig 4m-p) than O-systems in all seasons (see table S2). In summer and spring, L-systems, on average, have higher maximum (~40-50%; fig 4i-j) and mean average intensity (~5-15%; fig 4e-f), which is also true for extreme (top 5%) L-systems during autumn compared to their counterparts originating on the ocean (~20% and 30%, respectively). However, average O-systems, in autumn and also winter (in terms of precipitation intensity) have slightly higher rain rates compared to L-systems. Therefore, O-systems are more spatially concentrated with higher rain rate and smaller areas compared to L-systems during these seasons. In summer and spring, both types of systems (land and ocean) generally move towards the east-southeast. However, in autumn and winter, they have different directions. L-systems still tend to move towards east-southeast, but O-systems usually move northward.

Further detailed comparisons are also shown in figure S1 (area), S2 (max mean intensity) and table S4 in Online Resources 1 for L-systems that reach the ocean (LO-systems), L-systems that remain over land (LL-systems), O-systems reach the land (OL-systems) and O-systems remain over the ocean (OO-systems). The Results for all seasons show that, on average, the differences between LL- and OO-systems (first columns in figure S1 and S2; Online Resources 1) are much smaller than LO- and OL-systems (third columns in figure S1 and S2; Online Resources 1). For example, the mean area of LL-systems, on average, are ~15-50% larger than OO-systems in all seasons. However, these differences increase to more than 200% for the ones reaching the ocean and land, respectively.

Fig. 5 PDFs of system snapshot properties originating on land and transitioning to the ocean (panels in the first and third columns) and originating on the ocean and transitioning to the land (panels in the second and fourth columns). Solid and dashed lines are related to the part of the systems that are over land and over the ocean, respectively. S_no refers to the number of storms that start from land and reach the ocean or vice-versa, and S_snp_L and S_snp_O refer to the number of system snapshots over the land and the ocean, respectively. Except for the first column, all differences between land and ocean distributions are statistically significant at 0.01 level based on the Kolmogorov–Smirnov test.

Next, we examine how the characteristics of LO- and OL-systems change during the transition of systems between land and ocean, by comparing the PDFs of system snapshots over

land and ocean. Note that the term “system snapshot” here refers to the system at a specific time-
step. LO-systems during summer/spring, on average, have ~15-30% (table S3) higher max average
intensity over land than later over the ocean (fig 5c, g). However, during the autumn and winter,
these differences are smaller (fig 5k, o). Summer and spring OL-systems tend to be ~45% smaller
over the ocean (fig 5b, f) without much change in rainfall intensity (fig 5d, h). In addition, autumn
and winter OL-systems are also more spatially concentrated with ~15% higher max intensity (fig
5l, p) and 15-30% smaller sizes when they are raining over the ocean compared to when they are
over land (fig 5j, n). Note that there is not much change in mean area of LO-systems after hitting
the ocean (fig 5a, e, i, m).

Fig. 6. Average rainfall intensity variation during the storm lifetimes (represented by seven bins) for storms originating on land (red) and ocean (blue). Only storms lasting at least an hour have been selected in these plots. Note that all the storms last at least an hour are normalized (averaged) into seven bins (timestep). NL and NO refer to the number of selected storms over land and ocean, respectively. The shaded areas show the 5 to 95 percentile range and the dashed/solid lines are the medians. Note that the differences between land and ocean in all bins are statistically significant at 0.01 level based on Kolmogorov–Smirnov test.

Precipitation intensity varies during the lifetime of the precipitation systems. The magnitude of the change might differ in different seasons and according to their source of originations (from land or ocean). Here, we have normalized the systems that last at least an hour into seven bins to investigate the life cycle of precipitation systems in terms of precipitation intensity. To normalize the systems with more than seven bins, we have divided each system lifetime equally into seven parts and the data within each part are averaged.

Figure 6 shows that system intensity generally peaks early in the system lifetime during all seasons, though more clearly in the summer. In all seasons excluding winter, O-systems, on average, have lower average intensity during their lifetimes compared to their land counterparts. However, the opposite is true in winter, when O-systems (on average) are more intense in the beginning of their lifetimes. In addition, L-systems have a wider range of variability during their lifetimes compared to O-systems and this range of variability is highest during summer and lowest during the winter.

583 5.2. Diurnal cycle of object properties

584
585
586 Fig. 7 Diurnal cycle of object properties overall (black; panels a-d) and for different seasons
587 (panels e-h). The results are also presented over land and ocean for different seasons in panels i-x.
588 NL and NO show the number of objects in each season over land and ocean, respectively. The
589 uncertainty bands are shown in figure S5 in Online Resources 1.

590
591 The diurnal cycle varies with season and with the location of storms (land/ocean). Extreme
592 summertime objects have an afternoon peak around 15:00 Australian Eastern Standard Time
593 (AEST = UTC + 10 hr) in terms of size (fig 7e) and intensity (fig 7f, g). However, winter objects
594 don't have such a peak during the day (fig 7e-g). Note that the afternoon peak intensity (which
595 exists for all seasons except winter) is mostly related to intense objects over land. In all seasons

except winter, high-intensity objects over the ocean, on average, are more intense (~5-15%) around 20:00-09:00 AEST (fig 7j, 7k, 7n, 7o, 7r and 7s) compared to their land counterparts, but in the afternoon and evening, the opposite is true with a larger difference (up to 50%). During spring and summer, fast-moving ocean objects, on average, move faster (up to 20%) than land objects during 10:00-20:00 AEST with a peak around 15:00 AEST (fig 7l and 7p). However, during the other times of the day, extreme land objects have faster translation speeds of up to 20%. Note that in winter, these peaks are less clear and land objects are mostly faster than their ocean counterparts (fig 7x).

5.3. Clustering analysis

Large- or small-scale atmospheric conditions may result in different types of precipitation systems with unique characteristics over a specific region. Identifying these groups and their typical characteristics and frequency over the region helps us to better understand the rainfall climatology of the region and better investigate the effect of large- or small-scale drivers on rainfall over that region. Using clustering algorithms, we have grouped the systems with similar object-based properties over the study area. Here, we employed the Agglomerative clustering technique over the projected multi-dimensional object-based precipitation system data on a 2D map using t-SNE algorithm. The selected input system properties in the clustering algorithm should not be highly dependent on each other. Therefore, we have calculated the correlation between all pairs of the studied object properties to identify the dependent properties. Figure 8 shows the correlated object properties at the significance level of 0.01. The same results have been derived for system properties (not shown). By considering a threshold of 0.5 for correlation coefficient, we have found that area vs. volume discharge (fig 8a) and maximum intensity vs. average intensity (fig 8h) are highly dependent on each other and should not be used together as the input in the clustering algorithm. Based on this analysis, the selected input properties (those left after excluding volume discharge and average intensity) for the clustering algorithm are: 1) mean area, 2) mean translation speed, 3) max average intensity and 4) mean translation direction which is decomposed into x and y components and have been considered as two independent input variables in the clustering algorithm. Note that we have clustered the systems rather than objects, since the motivation here is to identify different groups of precipitation systems.

The bi-variate histograms in figure 8 also show that objects with higher intensities are generally larger in size (fig 8c and 8f). In addition, when the size of an object increases, the shape of the object (on average) tends to be more linear (fig 8d, 8e).

Fig. 8 Bivariate histograms for object properties. Tau (correlation coefficient) and P-value in the figures are calculated based on Kendall's tau method. All the relations shown are significant at 0.01 level.

634
635

636 Fig. 9 Panel (a) is the projected 5-dimensional object-based system data on a 2D map. The
637 colour on this map shows the density. Panel (b) shows the variation of CHI with the number of
638 clusters. Panel (c) represents the clustered groups of the 2d map (panel a) using the Agglomerative
639 method. Panels (d-h) show the PDFs of different properties for the clustered systems. The annual
640 cycle of each cluster is shown in panel (i).

641

642 The results show that there are five system clusters (types) with similar object-based
643 properties occurring over the study area. This number is based on the optimum value of CHI
644 against the number of clusters (fig 9b; for more details see section 4.2.2). Figure 9d-h show the
645 PDFs of system properties for different system types with similar quantitative characteristics that
646 have been identified using the Agglomerative and t-SNE algorithms over the study area. Based on
647 these results, the individual system types have the following characteristics:

- 648 • Type 1 (T1) systems have a peak frequency in autumn and include mostly middle size
649 systems (with an average size of ~133 km²) and have the lowest translation speeds (~23 km/hr)
650 but very high rainfall intensities (second-highest; with mean average intensity of ~5.4 mm/hr)
651 compared to other groups. Around 69% of these systems originate on the ocean and often stay over

the ocean (~56% of total) while moving towards the north. This type often features more isolated oceanic convection

- Type 2 (T2) systems often originate over land (54%) move south-eastward and often include the fastest systems (~53 km/hr) and appear in large sizes (~327 km²) but with low rainfall intensities (mean average intensity of ~4.3 mm/hr). They occur throughout the year with a frequency peak in spring.

- Type 3 (T3) systems mostly occur during winter with a frequency peak in June. They often originate on the ocean (66%) and remain over the ocean (58% of total) while moving northward. They often include the very slow systems (~29 km/hr) with the smallest sizes (~64 km²) and low intensities (mean average intensity of ~4.6 mm/hr) compared to the other types.

- Type 4 (T4) mostly occur during the summer over land (54%) and often includes the most extreme systems in terms of rainfall intensity (mean average intensity of ~8.15 mm/hr) and often appears in large sizes (260 km²) moving eastward with low translation speeds (~32 km/hr). Some of these storms resemble mesoscale convective systems.

- Type 5 (T5) systems mostly include very fast systems (47 km/hr) with small sizes (76 km²) and low rainfall intensities (4.6 mm/hr) that often occur during the winter, mostly originate on the ocean (64%) and stay over the ocean (58% of total) while moving northward.

Table S5 and S6 in the supplemental material present more detailed information about the system types. To further demonstrate the characteristics of each cluster, a video representing the typical systems for each cluster is provided in the supplemental material (Online Resources 2 or <https://www.youtube.com/watch?v=5o40u15iirc>).

Fig. 10 Selected regression coefficients for the relationship between climate mode indices and the object-based system properties in different months. The detail of selection criteria is explained in the manuscript. The coloured bars show the normalized coefficients that are significantly different from zero. Note that the colours represent the system types and are matched with the system types' colours in figure 9.

We also investigated whether significant relationships exist between system properties and climate mode indices. Although no statistically significant relationships were found when investigating all systems, we have found some significant relationships between climate indices

and system properties in each cluster (identified in the previous section) using a multiple regression model described in section 4.3. Based on this approach, 75 regression models have been produced (3 indices $\times$ 5 storm properties $\times$ 5 clusters; see figures S12-16). In order to identify robust associations, the coefficient for a given index in equation 11 must have the same sign (positive or negative) for at least five consecutive months and it must be significantly different from zero in at least three of these months. Since these climate indices often have impacts on weather for a period from 3-9 months, this restriction helps us to better exclude those short periods in which precipitation has a statistically acceptable link with climate indices but probably not in reality. Thus, from all of the results, only five regressions passed this criterion and are shown in figure 10. The results show that T3 and T5 systems have negative correlation with ENSO in cold season with lower rainfall intensity in El Niño and higher rainfall intensity in La-Niña (fig 10a, 10b). ENSO also shows a relationship with T1 and T3 mean translation speeds during the warm season with a positive correlation (faster in El Niño and slower in La-Niña; fig 10c, 10d). Finally, IOD has also shown to have a positive correlation with T1 mean translation speed from mid-summer to early winter (Feb, Apr and Jun; fig 10e). Note that in figure 10, all the coefficients have been normalized to derive the partial correlation between every index and system property according to equation 12.

5. Discussion

The results presented in Section 4.1 are broadly consistent with previous studies, but with some notable exceptions. For example, during summer, systems are mostly larger, move faster and are accompanied by higher rainfall intensities compared to the systems in winter (fig 2). This is in agreement with the previous studies over Australia reporting that severe thunderstorms are most prevalent in the warm season (Niall and Walsh 2005; Schuster et al. 2005; Davis and Walsh 2008; Warren et al. 2020). The extreme summer and spring systems in terms of rainfall intensity are more intense when they are raining over land between 10:00 to 20:00 (AEST; peaking in the afternoon) compared to when they are raining over the ocean, consistent with the diurnal cycle of surface temperature and the maximum availability of heating over land. The diurnal peak of severe thunderstorm over land during the warm season was also reported by Griffiths et al. (1993) in studying the severe thunderstorms in New South Wales, Australia and Schuster et al (2005) in studying the hail climatology of the Greater Sydney, Australia both using severe weather reports.

We have also found that there are more precipitation systems during autumn and winter than spring and summer. However, previous studies reported that thunderstorms are more prevalent during the warm seasons. The first reason behind this contradiction is that most of those studies were focused on the severe thunderstorms or storms with deep convective clouds and high storm tops that are often accompanied by electrification, which are less frequent during the cold seasons. In addition, they often employed ground observations that provide information for storms only over land (Niall and Walsh 2005; Schuster et al. 2005; Davis and Walsh 2008) whereas, based on our findings, autumn and winter systems mostly initiate from the ocean and tend to move northward, causing more precipitation over the ocean than land (see table S7). Thus, previous

studies using gauge data and reports omitted the storms over the ocean in these seasons. Using lightning records, Dowdy and Kuleshov (2014) also showed that a maximum in lightning activity during the cooler months occurs over the ocean to the east of Australia, which is consistent with our results. However, they reported a higher frequency of thunderstorms during the warm season. Since precipitation systems in cold season are often small-scale with low rainfall intensity, many of them are not accompanied by lightning. Therefore, a large number of systems over the ocean during this season are probably missed in the mentioned study.

We have calculated the weighted average wind direction based on the number of systems detected in each day at 700 hPa and 850 hPa in ERA5 Reanalysis data (Hersbach et al. 2020) (see fig S10 and S11; Online Resources 1) to examine whether the mean system directions are (on average) following the wind directions in different seasons. The results show that typical system directions only in summer and spring seem to be in agreement with climatological wind fields at 700 hPa in ERA5 and in autumn and winter it doesn't seem to agree well, especially over the ocean. However, The agreement in all seasons seems to be better when compared with 850 hPa wind fields since the north-westerly system directions (fig 2e, 2l) during these seasons are better matched with the wind directions and in autumn and winter the northward directions of systems agree better with wind direction at this pressure level. However, in winter the wind directions are slightly south westerly. Further investigations are required to find the reasons for differences between system movements and wind directions in these seasons.

In all seasons, land and ocean-originating systems tend to peak early in their lifetimes (fig 6) consistent with the findings of Ayat et. al. (2021b) and Prein et. al. (2017) over the United States. Additionally, we have found that this peak is more prominent during the summer for severe storms raining over land. Systems' characteristics also change during the transition of storms between land and ocean like the decrease in max intensity for summertime land-originating systems when moving over the ocean and wintertime ocean-originating systems when moving over land. These variations are probably related to a change in boundary layer instability, and shows the immediate effect of change in air mass characteristics (land/ocean) on the storms. These characteristics can include surface temperature and humidity, sea/land breezes and topographical interactions, the effects of elevated mixed layers advected over the coast, low-level wind shear and convergence.

Using clustering analysis, we have found that there are five precipitation system types with similar object-based properties over this region (fig 9) and described in detail in section 5.3. Among these clusters, three system types might be accompanied by high-impact weather, due to their special characteristics. The first system type (T1) mostly includes the slowest systems that have high rainfall intensities with average areas and mostly move towards the north-northwest with a peak frequency in autumn. These types of systems have less risk of flash floods in this region since they are often raining over the ocean and are not large in area. However, the ones that move toward the west-northwest and have enough area can create flash floods if they hit land, such as the high-impact event on 30 May 2011, with a dominant contribution of this type of system to flash flooding in some of Sydney's eastern suburbs (e.g., Zetland, Alexandria and Kingsford).

Another example is the event on 28 Feb 2014 with incidents of flash flooding have been reported across lake Macquarie. T2 systems mostly move towards the southeast and include the largest and fastest systems but with very low rainfall intensity occurring in every season with a peak frequency at the end of spring. This type of system can be accompanied by severe winds if the high upper-level momentum is transported to the surface via downdrafts. For instance, this contributed to the storm that occurred on 8 January 2003, and brought a severe wind gust with a maximum of 109 km/h. They also had a dominant contribution in the storm with the severe wind gust of 91 km/hr on 9 Feb 2017. However, due to their low rainfall intensity they may be accompanied by weaker downdrafts and associated outflow, and hence a lower likelihood of strong winds. Finally, T4 systems mostly occur in summer and include the extreme high-intensity storms that have very large sizes with slow translation speed. These characteristics of the storms in this group can create devastating flash and riverine floods in this region. Their dominant contribution in the East Coast Low event on 1 and 2 February 2005 caused flash flooding in Sydney with reports of 6 cm size hail. This type of system was also responsible for a severe storm on 25 Apr 2015 that caused hail and flash floods in this region.

Our results in investigating the relationships between climate mode indices and system properties are consistent with previous studies reporting a weak or no correlation between ENSO and extreme (Pepler et al. 2014; Ashcroft et al. 2019) or daily (Risbey et al. 2009) rainfall in coastal eastern and southeastern Australia. Similar results were also reported for extreme rainfall frequency from thunderstorms in southeast Australia (Allen and Karoly 2014; Dowdy 2020). However, system frequency is not studied here. While no relationship was found for all systems, we have found that the rainfall intensity in T3 and T5 system types (that are more frequent in winter) decreases during these events (fig 10a, b).

We have found relationships between some object-based system properties over the study area that have also been reported in previous studies over other regions. For example, we find that objects with large volume and size tend to be more linear and are accompanied by higher rainfall intensities (fig 7); this is consistent with the findings of Ayat et. al. (2021b) in comparing a merged ground radar product and a merged satellite precipitation product over the United States, and Prein et al. (2017) in simulating North American mesoscale convective systems with a convection-permitting climate model. Large-scale heavy storms over the study area fall in T2 and T4 system categories (all the top 1% of large-size systems are T2 (364 out of 400) or T4 (36 out of 400) systems) and looking at the 99.9th percentile of large-size objects, we find they are generally associated with upper-level troughs (see fig S17; Online Resources 1) and tend to be elongated/oriented parallel to the trough axis.

In summary, the results show that the precipitation system intensity variations are consistent with diurnal/seasonal cycles and for some storm system types are related to climate mode oscillations. However, other characteristics of the precipitation systems like size and translation speed do not seem to always follow the same relationship. This suggests that further investigations are required to find a more definitive answer to the effect of atmospheric parameter variations (e.g. temperature, humidity, etc.) on system properties other than intensity.

6. Conclusion

In this study, we establish an object-based precipitation system climatology using an S-band weather radar located near Wollongong, NSW with more than 20 years of records (1996-2018). The study area is the radar coverage region (including land and ocean), within 150 km of the radar. Here, we employed the Method of Object-based Diagnostic Evaluation (MODE) Time Domain (MTD) to detect and track the precipitation systems. Using this object-based approach helps us to better understand the climatology of precipitation system properties (other than rainfall intensity and frequency) that haven't been explored in the previous studies over the study area.

The extreme precipitation systems in terms of size, intensity and translation speed are more frequent during summer and spring. Precipitation systems in these seasons mostly originate on land, move towards the east-southeast, are larger, faster and more intense compared to the systems originating on the ocean. In these seasons, between ~10am and ~8pm (AEST), precipitation systems raining over land (wherever they originate) are often larger and have higher rain rate but move slower compared to when they are raining over the ocean (with a peak in rain intensity and translation speed in the afternoon that is consistent with the diurnal maximum of boundary layer instability). However, later at night into early morning, precipitation systems raining over the ocean are slower, larger and more intense compared to when they are over land.

Although severe storms are more frequent during summer and spring, typical storms in autumn have higher rainfall intensity compared to the other seasons. In addition, precipitation systems are more frequent in autumn and winter compared to summer and spring. During the cold season, precipitation systems mostly initiate from the ocean and tend to move northward, which causes more precipitation over the ocean than land. Ocean-originating systems during these seasons like summer and spring are typically smaller and move slower but have higher rainfall intensity than the land-originating systems which still tend to move east-southeastward.

The results show that the change in the air mass characteristics (land/ocean) can immediately affect the precipitation systems' properties. For instance, the land-originating systems that cross to the ocean in summer are more intense over land than ocean. However, in winter, ocean-originating systems that hit the land are more intense over ocean than land. These changes in precipitation systems' properties during their lifetimes might be related to the differences in surface temperature and humidity, sea/land breezes and topographical interactions, the effects of elevated mixed layers advected over the coast, low-level wind shear and convergence. Although the biggest driver is likely to be larger instability over the warmer surface, further research is needed to find a definitive answer.

We have found five types of precipitation systems with distinct object-based properties using clustering techniques. The first system type (T1) peaks in autumn and mostly includes small-scale and slow-moving systems but with high rainfall intensities, often moving northward over the ocean. This type of system has the potential to create flash floods when they move onshore. T2 systems are the largest and fastest systems with low rainfall intensities, often moving southeastward with a peak in spring. This system type can be accompanied by severe wind gusts. T3 systems, include the smallest size systems moving northward with low intensities and

translation speed and peak in winter. T4 systems include the most extreme precipitation systems in terms of rainfall intensity with large areas often moving slowly towards the east with a peak in summer, and can be a source of devastating flash and riverine floods over the study area in this season. Finally, T5 systems are wintertime small scale systems over the ocean, moving northward with high translation speeds. We also studied the connection between climate modes and precipitation systems' properties for different clusters using a linear multivariate approach and the results show that during El-Niño events in cold seasons, T3 and T5 systems have negative correlation with ENSO in cold season with lower rainfall intensity in El Niño and higher rainfall intensity in La-Niña. In addition, ENSO has association with on T1 and T3 system translation speeds during the warm season with a positive correlation (faster in El Niño and slower in La-Niña). Finally, IOD has also shown a positive correlation with T1 system translation speeds from mid-summer to early winter (Feb, Apr and Jun).

Although previous studies using pixel-based approaches have provided us with valuable information, the outcomes of this research show that the object-based approach can be a powerful means to better understand other aspects of the precipitation systems like storm size, translation speed, direction, aspect ratio, lifetime, track length, etc. which was not possible using pixel-based approach. In this study, we have conducted a comprehensive study to understand the precipitation system climatology. However, this study is limited to a specific region in Australia, and further research is needed to conduct the same study over the other regions or over a larger scale using regional/global datasets. In addition, there are lots of questions unanswered in understanding the precipitation system structures and the effects of parameters like temperature, humidity, topography, surface type, etc. on the precipitation system properties other than rainfall intensity, which might be better explored using an object-based approach.

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Availability of data and material: Radar data used in this study are available at https://geonetwork.nci.org.au/geonetwork/srv/eng/catalog.search#/metadata/f4093_2998_3846_6573.

Code availability: The codes that support the findings of this study are accessible from the following link: <https://github.com/H0omaN/MTD-Modified>

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