A Radar Object-Based Examination of Rain System Climatology and Including Climate Variability

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A radar object-based examination of rain system climatology and including climate variability

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1. Abstract

We know the climate is warming and this is changing some aspects of storms, but we have 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 storm 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. Storms 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 storm 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 storm types using a multivariate approach. This climatology for a variety of storm 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 is accompanied by 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 storm characteristics and their (local and remote) drivers in different seasons. Many studies have used 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 often unable to properly capture small scale storms like thunderstorms. Therefore, in order to capture these small scale storms using these datasets, researchers have tried to establish thunderstorm climatologies based on the concept of favourable conditions for thunderstorms, which usually includes 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 ERA-Interim reanalysis and reported observation data. They showed that these types of storms are more frequent in December during the afternoon, consistent with the seasonal and diurnal cycle of surface temperature and the maximum availability of heating. Although this approach provides valuable information, environmentally favorable conditions do not necessarily lead to a thunderstorm, causing a misestimation of the thunderstorm frequency. In addition, this approach only provides us with storm frequency and it is unable to provide information on other storm characteristics (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)) on the rainfall over Australia. Ashok et al. (2003) showed that IOD has significant negative partial correlations with rainfall over the western and southern regions of Australia using an atmospheric general circulation model. Allen and Karoly (2014) employed the ECMWF Interim Re-Analysis (ERA-Interim) data and have found that ENSO has a substantial impact on the spatial distribution of severe thunderstorm environments over the continent. 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 is 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 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 intensity and frequency, and the relationships between other characteristics of storms (i.e., size, shape, translation speed, etc.) and climate modes are not understood.

One way of studying the thunderstorm climatology is by measuring the occurrence of lightning using satellite instruments such as the Optical Transient Detector (OTD) and/or the Lightning Imaging Sensor (LIS). 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). A limitation of this approach is that it is unable to capture storms without lightning. Additionally, it is only able to provide information regarding storm frequency, not other information like rainfall intensity (Walsh et al. 2016).

Rain gauge data and reports of hail, tornado and wind gusts are other means of studying thunderstorm climatology 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 gust winds in some countries like Australia have a long-term record (Bureau of Meteorology 2021), which can provide valuable information for climatological 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 these types of data 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. Although gauge and reported data provide us with valuable information, the

distribution of recorded data is highly influenced by the local population (Allen 2018). In addition, gauge instruments are point measurements and sparse rain gauge networks often fail to observe the maximum rainfall (Ayat et al. 2018).

The limitations of previous approaches have led to the application of remotely-sensed datasets, which are a growing area of thunderstorm climatology. 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 the potential to study the thunderstorms occurring over 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 conduct thunderstorm climatology studies 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 quasi-spherical shape which produces distinct differential reflectivity values for dual-polarization radars compared to oblate rain droplets. 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), and found that, on average, damaging hail storms over Sydney occur 32 days per year with a peak during the warm season (November-March). 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. 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 us with 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 this research, we employ the Method of Object-based Diagnostic Evaluation (MODE) Time Domain (MTD), which is modified by the authors so as to handle splitting and merging of objects. We apply this to the Wollongong (near Sydney) radar, 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). An effort has been made to group the main contributing storms with similar object-based characteristics over this region using clustering algorithms followed by investigating 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, 150.87° 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 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 over the last 24 years. Initially, the radar operated on a 10-minute volume cycle with 16-level reflectivity data. 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, 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 the adjacent South Pacific Ocean.

Reflectivity data is transformed to rain rates using a fitted Z-R relationship derived from 9 years of hourly rain gauge data using the Camden Airport AWS (35.04° S, 150.69° E). The A and B coefficients for this relationship were 81 and 1.8 respectively. The maximum rainrate 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 2.5km constant radius of influence. The final grid has a horizontal resolution of 1 km and a domain size of 300 km by 300 km.

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 as precipitation echoes, while also being non-stationary, limiting the effectiveness of any algorithms to remove non-meteorological echoes from reflectivity data (fig S5a; 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 S5b; Online Resource 1) except some extremes in summer (fig S5d; Online Resource 1). 2) The days with extreme clutter were removed manually from the dataset using maximum daily reflectivity maps (see fig S4; 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, or Cfa 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 (Bureau of Meteorology 2016; Dare and Davidson 2015). The mean annual precipitation recorded at Observatory Hill (in Greater Sydney) and Wollongong University (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 (Bureau of Meteorology 2013). 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, in which case they are accompanied by long-lasting heavy rainfall and gusty winds (Bureau of Meteorology 2007). 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. However, precipitation over the coastal zone that includes our study area has shown little relationship (Timbal and Hendon 2011; Fita et al. 2017) Method

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

MTD is an extension for MODE to track the storm 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 storm. In this method, the “storm 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 “storm object” at each time-step has a unique label number unless it has overlap with another storm object at the previous time-step (each blob in figure 1b). In this case, it takes the label of the storm object at the previous time-step. If a storm-object has overlap with two (or more) storm objects in the previous time step (merging) or two (or more) objects have overlaps with a storm-object at the previous time step (splitting), the storm-object/storm-objects at the current timestep takes/take a new label. Based on these definitions, A “sequence of objects (or 3D objects)” is the connected storm 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 1b). Finally, a “storm” is a group of the 3D objects that are connected via split/merging events (The whole diagram in figure 1b).

Figure 1a 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 3D-object tracks. In this event, land-originating storms' parts had a southeastward direction and later were merged with the storms' parts that had formed over the ocean. Considering split/merge events in this event has shown how successfully this approach could separate storms' parts over land and ocean before merging which is not possible using the original version of MTD. In addition, with the help of the new approach in tracking the storms, it's possible to extract storm characteristics with more details from different parts of the storms and better calculate characteristics like translation speed, direction and track length during the lifetime of the storms with high rate of split/merge events.

In this research, we are studying the extracted characteristics related to "storms" and "storm objects" using the modified MTD method. 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 storm-object characteristics of interest in this study include: 1) area: the number of pixels in the storm object; 2) translation speed: the ratio of the distance between the volumetric centroid of two connected objects in time to the temporal resolution of the dataset; 3) maximum intensity: the maximum precipitation rate within a storm object; 4) object average intensity: the average precipitation rate of all cells within a storm object; 5) object volume discharge: the volumetric rain rate that passes through the storm object area during a specified period; 6) aspect ratio: the ratio of the minor and major axis of the fitted ellipse over the storm object; 7) object direction: the compass direction of the line connecting the centroids of two consecutive objects in a sequence, and finally, 8) orientation that is the compass direction of the major axis of the fitted ellipse.

The studied storm characteristics in this research include: 1) storm area: the average storm snapshot areas in the storm lifetime; 2) storm volume discharge: the average storm snapshot volume discharge in the storm lifetime; 3) storm average intensity: the average of precipitation rate in the storm lifetime; 4) storm max average intensity: the maximum of storm averaged intensity (calculated at each snapshot) in the storm lifetime; 5) storm translation speed: the area-weighted average translation speed of the storm snapshots in the storm lifetime; 6) storm direction: the area-weighted average direction of the storm snapshots in the storm lifetime; 7) storm contributing objects: The number of root storm objects in the storm graph diagram (e.g. in figure 1 storm object numbers 1, 2 and 3 are the root objects in the storm diagram) and 8) storm split/merge event number: the number of split/merge events in the storm lifetime. Note that no thresholds have been applied over the defined storm/storm-object properties in this study.

Fig. 1 Panel (a) shows the 3D-object tracks for storms that occurred on (2018-10-04; UTC). Panel (b) illustrates the diagram of a tracked storm with split/merge events. Note that each blob represents a storm object at each time step and each colour shows a sequence (or 3D) object.

4.2. Clustering Analysis

The aim of this section is to find storm clusters (types) with similar quantitative characteristics over the study area using both the Agglomerative clustering algorithm and the t-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 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 diverges 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 group in the beginning. Next, 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 S3; 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 storm-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 storm property by its maximum and standard deviation.

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 by increasing the number of clusters.

CHI is the ratio of between-cluster variance (VAR_B) to within-cluster variance (VAR_W):

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

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

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

Here, 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).

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 following equation:

$$tau = \frac{C-D}{C+D} \quad (4)$$

In this equation, C is the number of matched pairs and D is the number of mismatched pairs of the two variables.

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:

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

$$D_{n,m} = \sup_x |F_{1,n}(x) - F_{2,m}(x)| \quad (6)$$

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

Where $D_{n,m}$ denotes the KS statistic and n,m are the sizes of the two datasets. $F_{1,n}$ and $F_{2,m}$ 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 .

In order to model the relationship between two or more variables, in this research, we have employed the Ordinary least squares (OLS) method:

$$y = \beta X$$

$$(8)$$

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

$$(9)$$

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

Where 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.

An effort has been made in this study to investigate the relationships between climate indices (i.e., El Niño–Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), and Southern Annular Mode (SAM)) and storm 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. Equation 11 is the model representing the relationship between the three selected indices and each object-based storm 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.

$$\text{Storm Prop.} = C_0 + C_1 \times \text{Niño 3.4} + C_2 \times \text{IOD} + C_3 \times \text{SAM} \quad (11)$$

Where C_0 is the Month constant and C_1 , C_2 , C_3 are Niño 3.4, IOD and SAM coefficients, respectively. Note that, in this equation, each object-based property at every timestep is matched with its monthly climate indices.

The monthly time series of Niño 3.4, DMI and AAO from NOAA, which refer to ENSO, IOD and Southern Annular Mode (SAM) are accessible from the NOAA Physical Sciences Laboratory (information available online at <https://psl.noaa.gov/data/climateindices/list/>)

4. Results

The object-based storm properties are compared in different seasons in section 5.1 followed by the detailed analyses of the storms originating on land and ocean. Then, the diurnal cycles of storm/storm-object properties are analyzed in section 5.2. Finally, in section 5.3 the main contributing storms with similar object-based properties are clustered using clustering analysis, 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 storm-objects and 35,445 storms have been identified. From the detected storm-objects, 252,636, 277406, 371389 and 317356 objects are detected in spring (SON), summer (DJF), autumn (MAM) and winter (JJA), respectively. The corresponding numbers for storms are 8233, 8091, 10080, 9041.

389 5.1. Seasonal analyses of storm/storm-object properties

Fig. 2 Storm/storm-object property distributions for different seasons. Note that the bins in the x-axis are equally spaced in the logarithmic scale except panels e-l. Panels e, h and l are also presented in polar coordinates. Green, red, brown 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 storm direction in panel (l) refers to the direction of the storm motion, and all the angles shown in panels e, h and l are measured from the positive direction of the x-axis.

Figure 2 represents the PDFs of the storm and storm-object properties in different seasons extracted from the radar data. Storms in summer and spring tend to move towards the east-southeast (fig 2i), and are larger in size (fig 2a, 2p) and volume (fig 2p, 2q) compared to the autumn and winter storms which usually move northward. Comparing the mode of PDFs of

rainfall intensity (fig 2c, 2d, 2m, 2o) shows that typical storms in autumn are more intense compared to the other seasons. However, extreme rain intensity is higher the warmer the season, since storms with maximum intensity above 40 mm/hr (top 10% of storms in maximum intensity) during spring, summer, autumn and winter have occurred 1194, 1662, 1182 and 441 times, respectively, during the study timeframe.

In autumn, storms tend to move slower (fig 2f, 2n) and look more symmetric (fig 2i) than in other seasons. In summer, storm objects are mostly oriented near 315° from the positive x-axis while in autumn and spring the object orientation angles mostly change to 330° and in winter storm objects are mostly oriented west-east (fig 2h). Along with having larger and more severe storms in summer than in winter, summertime storms often include more contributing objects and split/merge events during their lifetimes (fig 2j, 2k). Although all of the mentioned differences are statistically significant based on Kolmogorov–Smirnov test, some storm properties clearly vary with seasons such as rainfall intensity and storm direction. However, there are some properties that look about the same in all four seasons like storm-object areas (fig 2a). Note that the differences between the storm size in different seasons are clearer in the storm area and volume PDFs (fig 2p, 2q).

Fig. 3 PDFs of storm properties for storms 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 storms originating on land and NO refers to the storms originating on the ocean.

We have also compared the typical and extreme storms' properties originating on land vs. ocean in different seasons by comparing their PDFs shown in figure 3. The results show that storms in spring and summer mostly initiate over land. However, in autumn and winter storms often originate over the South Pacific Ocean. Land-originating storms are typically larger (fig 3a-d) and move faster (fig 3n-q) than ocean-originating storms in all seasons. In summer and spring, typical land-originating storms have higher maximum (fig 3j-k) and average precipitation

intensity (fig 3e-f), which is also true for extreme land-originating storms during autumn compared to their counterparts originating on the ocean. However, typical ocean storms in autumn and also winter (in terms of precipitation intensity) have slightly higher rain rates compared with storms originating on land. Therefore, typical ocean-originating storms are more spatially concentrated with higher rainrate and smaller areas compared to land-originating storms. In summer and spring, both types of storms (land and ocean) mostly move towards the east-southeast. However, in autumn and winter, they have different directions. Land storms still tend to move towards east-southeast, but ocean-storms usually move northward.

Fig. 4 PDFs of storm snapshot properties originating on land and transitioning to the ocean (panels a-d) and originating on the ocean and hitting the land (panels e-l). Solid and dashed lines

are related to the part of the storms that are over land and over the ocean, respectively. St_no refers to the number of storms that start from land and reach the ocean or vice-versa, and St_snp_L and St_snp_O refer to the number of storm snapshots over the land and the ocean, respectively. All differences between land and ocean distributions are statistically significant based on the Kolmogorov–Smirnov test.

Next, we examine how storm properties change during the transition of storms between land and ocean. Land-originating storms during summer/spring have higher max intensity over land than later over the ocean (fig 4a, b). However, during the autumn and winter, these differences are smaller (fig 4c, d). Summer and spring storms originating over the ocean and reaching land tend to be smaller (fig 4e, f) without much change in rainfall intensity (fig 4i, j). In addition, autumn and winter ocean-originating storms (that reach the land) are also more spatially concentrated (with higher max intensity (fig 4k, l) and smaller sizes) when they are raining over the ocean compared to when they are over land (fig 4g, h).

Fig. 5 Average rainfall intensity variation during the storm lifetimes (represented by seven bins) for storms originating on land (red) and ocean (blue). Only storms with more than seven timesteps have been selected in these plots. Note that all the storms with more than 7 timesteps 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.

Precipitation intensity varies during the lifetime of the storms, as shown in Fig. 5. Storm intensity generally peaks early in the storm lifetime during all seasons, though more clearly in the summer. In all seasons excluding winter, ocean-originating storms, on average, have lower average intensity during their lifetimes compared to their land counterparts. However, the

opposite is true in winter, when ocean-originating storms (on average) are more intense. In addition, land-originating storms have a wider range of variability during their lifetimes compared to ocean-originating storms and this range of variability is highest during summer and lowest during the winter.

5.2. Diurnal cycle of storm/storm-object properties

Fig. 6 Diurnal cycle of storm-object properties overall (black; panels a-d) and for different seasons (panels e-j). The results are also presented over land and ocean for different seasons in panels k-z. NL and NO show the number of storm objects in each season over land

and ocean, respectively. The shaded area shows the range from 5-95% and the dashed/solid lines show the median.

The diurnal cycle varies with season and with the location of storms (land/ocean). Extreme summertime storm-objects have an afternoon peak around 5:00 UTC (15:00 Australian Eastern Standard Time; AEST) in terms of size (fig 6e) and intensity (fig 6f, g). However, winter storms don't have such a peak during the day (fig 6e-f). Note that the afternoon peak intensity (which exists for all seasons except winter) is mostly related to intense storm-objects over land. In all seasons except winter, high-intensity storm-objects over the ocean are more intense around 10:00-23:00 UTC (20:00-09:00 AEST; fig 6l, 6p, 6t, 6m, 6n and 6q) compared to their land counterparts, but in the afternoon and evening, the opposite is true. During spring, summer and autumn, fast-moving ocean storm-objects move faster than land storm-objects during 0:00-10:00 UTC (10:00-20:00 AEST) with a peak around 5:00 UTC (15:00 AEST; fig 6n and 6r). However, during the other times of the day, extreme land storm-objects have faster translation speeds. Note that in winter, these peaks are less clear and land storm-objects are mostly faster than their ocean counterparts (fig 6z).

5.3. Clustering analysis

Using clustering algorithms, we have grouped the storms with similar object-based properties over the study area. Here, we employed the Agglomerative clustering technique over the projected multi-dimensional storm data on a 2D map using t-SNE algorithm (more details in section 4.2). The selected input storm 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 storm-object properties to identify the dependent properties. Figure 7 shows the correlated properties at the significance level of 0.01. By considering a threshold of 0.5 for correlation coefficient, we have found that area vs. volume discharge (fig 7a) and maximum intensity vs. average intensity (fig 7h) 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 for the clustering algorithm are: 1) storm area, 2) storm translation speed, 3) storm max intensity and 4) storm direction which is decomposed into x and y components and have been considered as two independent input variables in the clustering algorithm.

The bi-variate histograms in figure 7 also show that storm-objects with higher intensities are generally larger in size and volume (fig 7b, 7c, 7f and 7g). In addition, when the size of the storm-objects increases, the shape of the storm-objects (on average) tends to be more linear (fig 7d, 7e).

Fig. 7 Bivariate histograms for storm-object properties. Tau (correlation coefficient) and P-value in the figures are calculated based on Kendall's tau method

Fig. 8 Panel (a) is the projected 5-dimensional storm data on a 2D map. The colour on this map shows the density. Panel (b) shows the variation of CHI with the number of clusters. Panels (c) represents the clustered groups of the 2d map (panel a) using the Agglomerative method. Panels (d-h) show the PDFs of different properties for the clustered storms. The annual cycle of each cluster is shown in panel (i).

The results show that there are five storm clusters (types) with similar object-based properties occurring over the study area. This number is based on the optimum value of CHI against the number of clusters (fig 9b; for more details see section 4.2.2). Figure 8d-h shows the PDFs of storm properties for different storm types with similar quantitative characteristics that have been identified using the Agglomerative and t-SNE algorithms over the study area. Based on these results, the detected storm types have the following characteristics:

- Type 1 (T1) storms have a peak frequency in autumn and include mostly average size storms with the lowest translation speeds but very high rainfall intensities compared to the other groups. They often move towards the north (over the ocean) to the northwest (hit the land)

- Type 2 (T2) storms often move south-eastward and include the fastest and largest storms but with low rainfall intensity. They are frequent during the whole year with a frequency peak in spring
- Type 3 (T3) storms mostly occur during winter with a frequency peak in June, mostly moving northward over the ocean, and include the very slow storms with the smallest size and low intensity compared to the other types.
- Type 4 (T4) includes the most extreme storm in terms of rainfall intensity and often appears in large sizes moving eastward with low translation speed. They mostly occur during the summer.
- Type 5 (T5) storms mostly include very fast storms with small sizes and low rainfall intensities that often occur during the winter, mostly moving northward (over the ocean).

To further demonstrate the characteristics of each cluster, a video representing the typical storm for each cluster is provided in the supplemental material (Online Resources 2).

Fig. 9 Selected regression coefficients for the relationship between climate mode indices and the object-based storm 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 storm groups and are matched with the groups' colours in figure 8.

We also investigated whether significant relationships exist between storm properties and climate mode indices. Although no statistically significant relationships were found when investigating all storms, we have found some significant relationships between climate indices and storm 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). In order to identify robust associations, we have identified instances when at least five coefficients in a row have the same sign (positive or negative), and among them at least three are significantly different from zero. 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 9. The results show that during El-Niño events in cold seasons, T3 and T5 storms have negative correlation with ENSO in cold season with lower rainfall intensity in El Niño and higher rainfall intensity in La-Niña (fig 9a, 9b). ENSO also has an impact on T1 and T3 storms' translation speed during the warm season with a positive correlation (faster in El Niño and slower in La-Niña; fig 9c, 9d). Finally, IOD has also shown to have a positive correlation with T1 storms' translation speed from mid-summer to early winter (Feb, Apr and Jun; fig 9e). Note that in figure 9, all the coefficients have been normalized to derive the partial correlation between every index and storm property as below:

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

Where σ is the standard deviation in this equation, “index coefficient” refers to any calculated coefficient from equation 11 and “index normalized coefficient” is the partial correlation between every index and storm property.

5. Discussion

The results presented in Section 4.1 are broadly consistent with previous studies, but with some notable exceptions. For example, during summer, storms are mostly larger, move faster and are accompanied by higher rainfall intensities compared to the storms 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 storms 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 reported data.

Although previous studies reported that thunderstorms are more prevalent during the warm seasons, we have found that there are more storms during autumn and winter than spring and summer. A reason behind this contradiction is that most previous studies employed ground observations that provide information for storms only over land (Niall and Walsh 2005; Schuster et al. 2005; Davis and Walsh 2008), and, based on our findings, autumn and winter storms mostly initiate from the ocean and tend to move northward, causing more precipitation over the ocean than land. Thus, the previous studies have not captured the storms over the ocean in these seasons. In addition, most of the previous 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. 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 storms in cold season are small-scale with low rainfall intensity, probably many of them are not accompanied by lightning to be captured by the sensors. Therefore, a large number of storms over the ocean during this season are probably missed in the mentioned study.

We have calculated the average wind direction during the rainy days (based on radar data) at 700 hPa and 850 hPa in ERA5 Reanalysis data (see fig S6 and S7; Online Resource 1) to examine whether the storm directions are (on average) following the wind directions in different seasons. The results show that typical storm direction in summer and spring seems to be in agreement with climatological wind fields at 700 hPa in ERA5. This agreement seems to be even better when compared with 850 hPa wind fields since the north westerly storm directions (fig 2e, 2l) during these seasons are better matched with the wind directions at this pressure level. However, in autumn and winter, it doesn't seem to agree well, especially over the ocean. Storms in these seasons mostly move northward over the ocean (fig 2e, 2l). However, the average wind directions in these seasons are south-westerly. A reason might be the climatological conditions during the cold season are not supportive of isolated offshore showers/storms which are more frequent in these seasons. However, further investigations are required by conducting a detailed comparison of wind and storm directions.

In all seasons, land and ocean-originating storms 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. Storm characteristics also change during the transition of storms between land and ocean like the decrease in max intensity for summertime land-originating storms when moving over the ocean and wintertime ocean-originating storms when moving over land. These variations are probably related to a change in boundary layer instability in this process, 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 storm types with similar object-based properties over this region and described in detail in section 5.3. Among these clusters, three storm types might be accompanied by natural disasters, due to their special characteristics. The first storm type (T1) mostly includes the slowest storms that have high rainfall intensities with small areas and mostly move towards the north-northwest with a peak frequency in autumn. These storms can create flash floods if they hit the land like the high impact event that occurred on 30 May 2011 with a dominant contribution of this type of storm and led to flash flooding in some of Sydney's eastern suburbs (e.g., Zetland, Alexandria and Kingsford). T2 storms mostly move towards the southeast and include the largest and fastest storms but with very low rainfall intensity occurring in every season with a peak frequency at the

end of spring. This type of storm can be accompanied by severe winds. For instance, they contributed to the storm that occurred on 8 January 2003, and brought a severe wind gust with a maximum of 109 km/h. Finally, T4 storms 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 (fig 8). 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.

Our results in investigating the relationships between climate mode indices and storm properties are consistent with the previous studies over the eastern and southeastern parts of Australia. Those studies have reported a reduction in rainfall intensity during El-Niño events in the cold season (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). While no relationship was found for all storms, we have found that the rainfall intensity in T3 and T5 storm types (that are more frequent in winter) decreases during these events (fig 9a, b).

We have found that there are relationships between some object-based storm properties over the study area that have also been reported in previous studies over other regions. For example, we find that storm 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 mostly fall in T2 and T4 storm categories, and typical T2 and T4 storms showed that they are mostly frontal systems that elongated/oriented parallel to the front borders.

In summary, the results are showing that the storm intensity variations are consistent with diurnal/seasonal cycles and are related to climate mode oscillations. However, other characteristics of the storms like storm 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 parameters variations (e.g. temperature, humidity, etc.) on storm properties other than intensity.

6. Conclusion

In this study, we establish an object-based storm climatology using an S-band weather radar located near Wollongong, NSW (34.26° S, 150.87° E, 471 m altitude) 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 storms. Using this object-based approach helps us to better understand the climatology of storm properties (other than rainfall intensity and frequency) that haven't been explored in the previous studies over the study area.

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

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

The results show that the change in the air mass characteristics (land/ocean) can immediately affect the storm properties. For instance, the land-originating storms that cross to the ocean in summer are more intense over land than ocean. However, in winter ocean originating storms that can reach land are more intense over ocean than land. These changes in storm properties during the storm 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. However, further research is needed to find a definitive answer.

We have found five types of storms with distinct object-based properties using clustering techniques. The first storm type (T1) peaks in autumn and mostly includes small-scale and slow-moving storms but with high rainfall intensities, often moving northward over the ocean. This type of storm has the potential to create flash floods when they move offshore. T2 storms are the largest and fastest storms with low rainfall intensities, often moving southeastward with a peak in spring. This storm type can be accompanied by severe gust winds. T3 storms, include the smallest size storms moving northward with low intensities and translation speed and peak in winter. T4 storms include the most extreme storms 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 storms are wintertime small scale storms over the ocean, moving northward with high translation speeds. We also studied the connection between climate modes and storm properties for different clusters using a linear multivariate approach and the results show that during El-Niño events in cold seasons, T3 and T5 storms 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 an impact on T1 and T3 storms' translation speed 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 storms' translation speed 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 storms 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 in understanding the storm climatology. However, this study is limited to a specific region in Australia, and further research is needed to do 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 storm structures and the effects of parameters like temperature, humidity, topography, surface type, etc. on the storm properties other than rainfall intensity, which might be better explored using an object-based approach.

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Code availability: The codes that support the findings of this study are available upon request from the corresponding author.

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