Document addressing reviewer comments

Dear editor, I have read accurately the manuscript and I found some criticalities that, in my opinion, should be solved before considering it for publication. In the following you can see my comments for the Authors.

Dear Authors, I have read accurately your manuscript and I found some criticalities that, in my opinion, should be solved.

Dear Reviewer, thank you for your valuable comments which helped us to improve quality of the manuscript. All your comments have been addressed in a revised version of the manuscript. We hope you will find this revision satisfactory.

First of all, at the beginning of the manuscript could be useful a table with the acronyms used in the text.

Addressed. An acronym table has been added below the abstract.

Section 1

Line 29: please specify the scale of intensity of TCs.

Addressed. The wind speed threshold for the 4-5 categories mentioned has been provided along with the scale used (Saffir-Simspon scale).

Lines 42-47: I maintain that could be useful a map showing the LGAs and Australian States (WA, NT, SA, QLD, NSW, VIC, and TAS) and some statistics on LGAs (e.g. number of LGAs, minimum, maximum, mean, and median extension). I suggest adding a study area section describing the physical and economic characteristic of Australia and all the toponyms cited in Section 3. Moreover, you do not explain at all the TC risk in Australia. It is important to add a part (may be in the study area section) describing the TC risk in Australia.

Addressed. A study area section has been added, with a map of Australian states and territories, major cities as well as a general characteristics table of each state.

Lines 53-68: It is not clear if in your study the analysed risks are caused by TCs. It is a cascade approach or not? I do not understand why and how it is possible to obtain TC risk combining surge, flood, wind, and landslide risks.

Addressed. This is clarified in the revised manuscript, specifying it is referring to TC-induced surge/flood/wind/landslide. All four TC-induced hazards are used in the calculation of their hazard specific risk (e.g. TC wind risk, TC flood risk, etc.).

Section 2

In my opinion in this section must be added a short part describing the difference among variables, indicators, and indexes. May help citing the “Pyramid of Information” of Hammond et al. (1995) or explaining better the IRDS that you cite in your paper.

Addressed. The three tiers/stages of create a risk index are detailed in new figure 3, with additional paragraph.

Moreover, I maintain that the table in Appendix may be reported in Section 2 and I suggest adding in the table the data format and resolution. In addition, I suggest explaining better these data in Section 2.1.

Addressed. The appendix data table has been moved into section 2 and has a new column with data format and resolution.

Lines 70-75: If I understand correctly, you started from hazard, exposure, and vulnerability indicators that were combined to obtain hazard, exposure, and vulnerability indexes by using equal weighting for exposure and Pareto front-ranking for vulnerability (and for risk?). Consequently, I suppose, you obtained surge, flood, wind, and landslide risks. And, finally, combing these risks you obtained TC risk. It is correct? Please explain it better. In my opinion the sentence “This data was then joined to LGA map shapefiles in ArcGIS Pro” may be changed in “This data was then combined to LGA map shapefiles in ArcGIS Pro”, because “join” is a particular GIS command.

Correct. This is clarified with the new diagram explaining the process. GIS jargon terms have been replaced with more general terms.

I maintain that Figure 1 do not explain in a correct way the risk mapping process. I suggest separating the part of the figure concerning the four term of equation 1 (risk, hazard, exposure, and vulnerability), as well as the different considered risks (surge, flood, wind, landslide, and TC). Moreover, the figure does not explain clearly the process of transforming the indicators to indexes. I suggest modifying the figure and explaining it analytically. Additionally, I suggest explaining briefly the Pareto ranking and the Figure 2 that, in my opinion, it is not clear. Consequently, I suggest re-writing the Section 2.3.

Addressed. Old Figure 1 has been removed and replaced with Figure 3 which separates each process. More accompanying paragraphs are added to walk readers through the process.

Section 3

The acronyms of the Australian states are not always evident in the maps. Please modify the maps accordingly.

Addressed. Section 2 (study area) has been added with Figure 1 which labels the boundaries of each state and territory.

You cited Pibara region, Mount Isa LGA, major coastal cities, major cities, inner cities, mining industries, urban areas, Maralinga Tjarutja LGA, Darwin, Great Diving Range, Tiwi and Mornigton Islnds, Bisbane, Cairns. Where are located these areas?

Addressed. Maps have now been annotated on most relevant figure where these locations are referenced (Pilbara, Maralinga Tjarutja, Townsville, Tiwi Islands, Mornington Island). Major cities have been highlighted in Figure 1. Some previous location names have been swapped out for descriptions of their location instead.

Overall, in my opinion the manuscript needs to be improved before considering it for publication.

Addressed. Major revision was undertaken to improve results and presentation.

Multi-hazard Tropical Cyclone Risk Assessment for Australia

Cameron Do and Yuriy Kuleshov

Natural Hazards and Earth System Sciences https://www.natural-hazards-and-earth-system-sciences.net/

Abstract

Tropical cyclones (TCs) have long posed a significant threat to Australia's population, infrastructure, and environment. This threat may grow under climate change as projections indicate continuing sea level rise and increases in rainfall during TC events. Previous TC risk ~~reduction~~ assessment efforts have focused on the risk from wind, whereas a holistic approach requires multi-hazard risk assessments that also consider impacts of other TC-related hazards. This study assessed and mapped TC risk nationwide, focusing on the impacts on population and infrastructure from the TC-related hazards of wind, storm surge, flooding and landslides. Risk maps were created at the Local Government Area (LGA) level for all of Australia, using collated data on multiple hazards, exposure and vulnerability. The results ~~study~~ demonstrated that the risk posed by all hazards was highest for coastal LGAs of eastern Queensland and New South Wales followed by medium risk across Northern Territory and north-west of Western Australia.~~, with flood and landslide hazards also affecting several inland LGAs.~~ Further enhancement ~~improvement~~ and validation of risk maps developed in this study will provide decision-makers with the information needed to reduce TC risk, save lives and prevent damage to infrastructure.~~ The resulting maps of risk will provide decision-makers with the information needed to further reduce TC risk, save lives, protect the environment, and reduce economic losses.~~

Comment [CD1]: Reviewer: acronym table

Acronyms

ABS	Australian Bureau of Statistics
LGA	Local Government Area
NSW	New South Wales
NT	Northern Territory
QLD	Queensland
SEIFA	Socio-Economic Indexes For Areas
SA	South Australia
TAS	Tasmania
TC	Tropical Cyclone
VIC	Victoria
WA	Western Australia

1. Introduction

Tropical Cyclones (TCs), also known as hurricanes or typhoons, are powerful and highly destructive meteorological hazards. Since 1970, almost 2,000 natural disasters have been attributed to TCs, which has led to over 700,000 deaths worldwide (World Meteorological Organisation, 2021). Costing about U.S.$26 billion annually in global damages (Mendelsohn et al., 2012), their impact is expected to multiply to U.S.$60 billion annually by 2100 (Bakkensen and Mendelsohn, 2019).

The proportion of intense TCs (Saffir–Simpson scale categories 4-5 with ~~>209km/h~~ 1-minute maximum sustained winds >209km/h) and peak wind speeds of the most intense TCs are projected to increase at the global scale with increasing impact of global warming (high confidence) (IPCC, 2022) ~~(IPCC AR6)~~ ~~(IPCC, 20221)~~. The potential of more destructive TC events will require updating and enhancement of existing risk reduction strategy. The Sendai Framework for Disaster Risk Reduction provides a structure for reducing disaster damages and increasing resilience to hazards including TCs (Bennett, 2020). One mechanism they encourage in Goals 18 and 24 is the distribution of multi-hazard risk information such as risk assessments.

Risk assessments combine hazard information with human activity, infrastructure and natural resources to determine the possible impacts of hazardous events (Belluck et al., 2006; National Research Council, 1991) and make informed choices for risk management in the most exposed and vulnerable regions (Aguirre-Ayerbe et al., 2018). Disaster risk is defined as the probability of harmful consequences, or significant losses, resulting from interactions between a hazard, and the local exposure and vulnerability to that hazard (Crichton, 1999; Downing, 2001).

As Local Government Areas (LGAs) are ~~the~~ one of the smallest government decision-making bodies with available census data~~y~~, information is sought to be provided on that scale. Risk assessments are a foundation for early warning systems to raise alerts of potential impacts, and to provide evidence for the prioritisation of funds and resources to areas in advance of any hazardous events. While the climate continues to change alongside evolving human activity, risk assessments must likewise be regularly updated to stay accurate and useful as a tool for disaster risk reduction (Peduzzi et al., 2012).

For TCs, the four main hazards are the destructive winds, associated storm surge, flooding from associated heavy rainfall, and landslides on steep terrain as soils saturate (Murray et al., 2020). TCs and other natural hazards are becoming increasingly recognised as multi-hazardous in nature (Scawthorn et al., 2006) (Scawthorn et al., 2006a). These hazards impact regions differently and their effects can compound to cause even greater damage (Gori et al., 2020).

While TCs can cause damage through different hazards, such as gale-force winds, storm surge or flooding, the communication of TC intensity and categorisation places emphasis on wind speed (Lavender and Mcbride, 2020). This is partially due to the availability of wind measuring technology and the relative ease to quantify wind. Publicly available warnings and forecasts are focusing on wind speeds, ultimately portraying the message that winds are the hazard to be most wary of. The literature however suggests the TC-induced impacts of storm surge and flooding contribute to the most human lives lost and infrastructure damage (Mendelsohn et al., 2012; Zhang et al., 2008). Although some studies have included multi-hazard aspects of TCs (Burston et al., 2017) (Burston et al., 2017b)~~,~~ presenting different hazard models for TC-induced storm surge, wind and flooding, these studies do not complete the story of combining hazard with exposure and vulnerability to map risk. Similarly, within the literature, there are many examples of standalone exposure or vulnerability index assessments for TCs (Marín-Monroy et al., 2020; Bathi and Das, 2016; Amadio et al., 2019). This gap indicates compelling scope to develop a multi-hazard TC risk assessment that can differentiate the extent and severity of TC-~~related~~ induced hazards.

This study will address this gap and strengthen TC risk information for the Australian region. Multi-hazard risk is assessed and visualised through ~~interactive~~ maps which show LGA categorisation, alongside hazard, exposure, and vulnerability layers. As a risk assessment's usefulness relies on how they are tailored for ~~a~~ specific users ~~audience~~ or applications, the method proposed in this study serves as a proof of concept that can be altered in future iterations for tailored use.~~.~~

2. Study area

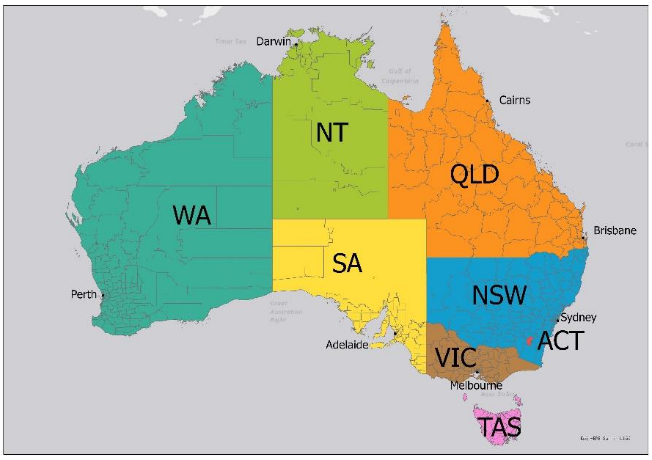

Figure 1. Map of study area, state, and territory boundaries as well as Local Government Area (LGA) divisions and major cities. States and territories: Western Australia (WA), Northern Territory (NT), Queensland (QLD), South Australia (SA), New South Wales (NSW), Australian Capital Territory (ACT), Victoria (VIC) and Tasmania (TAS) are labelled.

Table 1. Comparison table of each Australian states general characteristics including total area, real GSP and population (Australian Bureau of Statistics, 2020-2021)

STATE	TOTAL AREA	Number of LGAs	Avg. area per LGA	GSP ($million)	Population	GSP per capita ($)
Australia Capital Territory (ACT)	2358	1	2358.172	433740	431483	100523
New South Wales (NSW)	800811	130	6160.083	6336350	8172561	77532
Northern Territory (NT)	1348094	18	74894.13	261810	246565	106183
Queensland (QLD)	1730172	78	22181.69	3689770	5194884	71027
South Australia (SA)	984275	71	13863.03	1149210	1770794	64898
Tasmania (TAS)	68018	29	2345.443	340830	541499	62942
Victoria (VIC)	227496	80	2843.695	4682640	6661697	70292
Western Australia (WA)	2526646	137	18442.67	3206530	2670231	120084

Australia is a country with a long coastline and ~~with~~ much of its northern states commonly impacted by ~~tropical cyclones~~TCs. An average of 12 TCs form in the Australian region annually (however,

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interannual variability is high ranging from 19 TCs in 1983/84 to 3 TCs in 2015/16, for records examined from 1970/71 to 2019/20 TC seasons (Kuleshov et al., 2020)), with 5 making landfall on average (Mortlock et al., 2018). In the last few decades, several severe TC events have destroyed infrastructure and caused billions of dollars in losses, including TC Larry (2006), TC Yasi (2011) and TC Debbie (2017).

Figure 1 shows the boundaries of each state and territory as well as the outline of Local Government Area (LGA) divisions within. Table 1 summarises key traits of each state such as their total area, real Gross State Product (GSP) and population. From the T~~t~~able 1 it can be seen that NSW and VIC are the states with the highest GSP (monetary measure of state output), as well as highest populations. For TC-related impacts however, we are most concerned with ~~interested in~~ the northern states that are expected to more commonly be impacted by TC events. QLD and WA therefore stand out as the next most important states with next highest GSP and populations. Important to note however is the size of QLD and WA states and much higher average area per LGA, meaning GSP contribution and populations are likely to be much more spread out.

~~2.~~3. Data and Methodology

To calculate the multi-hazard risk of TCs to Australia, hazard, ~~exposure~~exposure, and vulnerability datasets were chosen and sourced. This data was then ~~joined~~ combined to LGA map shapefiles in ArcGIS Pro. To calculate exposure and vulnerability indexes from multiple indicators, equal weighting was used for exposure, while Pareto front-ranking was used for vulnerability. Combined with hazard values for each LGA, exposure and vulnerability indexes were used to calculate risk using equation 1:

$$\text{Risk} = \text{Hazard} \times \text{Exposure} \times \text{Vulnerability} \quad (1)$$

~~1.1.~~ 3.1 Selection of indicators

Table 2. Data table for LGA risk analysis. Links are provided for the data sources as well as the year that the dataset was last updated.

Indicator	**Dataset used**	**Source**	**Year**	**Data format and resolution**
Hazard				
Surge hazard	Global tropical cyclone storm surge run-up height, 100yr return period	GAR Atlas (2015)	2015	Point data (every 1km along coastline)
Flood hazard	Australian flood depth inundation, 100yr return period	GAR Atlas (Rudari et al., 2015)	2015	Raster data (1km)

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Wind hazard	Australian tropical cyclone wind, 100yr return period	Geoscience Australia (Arthur, 2018)	2018	Raster data (2km)
Landslide hazard	Global landslides hazard	ThinkHazard! (Arup, 2020)	2020	Raster data (1km)
LGA Exposure				
Population	Recorded total number of people living in each LGA.	ABS Census data	2016	Tabular data (LGA resolution)
Public hospital	Point feature layer of public hospitals around Australia	ArcGIS Online Dataset	2019	Point data
Substations	Point feature layer of power substations around Australia	Geoscience Australia	2016	Point data
Powerlines	Line feature layer of powerlines around Australia	Geoscience Australia	2016	Line data
LGA Vulnerability				
IRSD	Summary statistic for socioeconomic status,	ABS Census data	2016	Tabular data (LGA resolution)
No vehicle homes	Percentage of households within each LGA that owns zero vehicles.	ABS Census data	2016	Tabular data (LGA resolution)
Vulnerable age groups	Percentage of LGA population that is under 15 or over 65	ABS Census data	2016	Tabular data (LGA resolution)
Shape layers				
LGA polygon layer	Shapefile containing the size of each LGA as of 2016	ABS Australian Statistical Geography Standard	2016	Polygon data (LGA resolution)

Hazard

The main identified hazards of TCs include storm surge, winds, landslides, and floods. The ~~100 year~~100-year return period was chosen to represent the current long-term probability ~~danger~~ of these hazards occurring. ~~in the near future.~~ Of note is that these probabilities may change in the future with studies predicting increased storm surge levels (high confidence) and increased TC-related precipitation (medium-high confidence) due to climate change (Cha et al., 2020).

Storm surge data was acquired from GAR Atlas' risk and data platform, which mapped TC storm surge height as point data roughly along the Australian coastline every 1km. TC wind data was sourced from Arthur (2018) and came as high-resolution raster data over Australia and its northern waters. Flood data was sourced from Rudari et al. (2015) as high-resolution raster data representing riverine flooding only. Thus, non-null values tended to only appear near riverine systems and catchments. Similarly, landslide data from Arup (2020) was in the raster format with mostly null values apart from specific locations with significant landslide hazard.

Storm ~~{Arthur, 2018 #181@@author-year}and wind datasets were specifically designed for TCs (Cardona et al., 2014; Arthur, 2021)~~surge and wind~~, and~~ spatial mean values were calculated over each LGA. For flood and landslide hazards the original datasets did not consider solely TC induced floods/landslides. Thus, the flood and landslide hazards were weighted towards TC prone regions by multiplying values by the TC wind raster dataset. Weighted flood and landslide values were then summed over LGAs as there were many null values. Greater than zero values exist only around water catchments and rivers for floods, and around mountain regions for landslides. Thus, LGAs with higher flood and landslide values have more of these prone environments in total rather than a higher areal proportion.

Exposure

Exposure indicators of population, hospitals, substations, and power lines were chosen to represent physical assets of human life, as well as systems and infrastructure that are important in the case of emergency disaster events (hospitals, power). Failure to maintain the function of lifeline infrastructures such as hospitals and power can lead to exacerbated negative impacts (Ju et al., 2019). These chosen indicators aim to spatially describe which LGA regions have more exposed assets relative to the rest of the country. Electrical substations provide power as critical infrastructure and are strategically placed to meet demand. Similar reasoning influenced the choice of public hospitals and powerlines.

While population density data of each LGA was found in tabular form from the Australian Bureau of Statistics (ABS), the remaining exposure indicators' raw format was as point or line shapefiles displayable in ArcGIS Pro. Thus geoprocessing tools such as spatial join were used to count the number of public hospitals in each LGA. Using absolute measurements can be inappropriate when considering regions of different sizes (Rygel et al., 2006), thus these counts were then divided by LGA area to give a density value similar to that of population density.

Vulnerability

Vulnerability indicators were chosen to represent regions most susceptible to high impact from a TC event occurring in the vicinity. Measures of socioeconomic status are commonly used to describe vulnerability to natural hazard events (Mitsova et al., 2018; Lianxiao and Morimoto, 2019) and the Index of Relative Socioeconomic Disadvantage (IRSD) has been used in earlier studies ~~previous literature~~ for the Australian region (Rolfe et al., 2020). It summarises variables about the social and economic conditions of households. The more disadvantaged a region is socioeconomically, the more likely it will be more impacted by TCs, due to factors such as lower income, having families with only one parent or having a higher percentage of people that have English as a second language. The 'no vehicle homes' indicator was derived by calculating the percentage of homes with no vehicles, and the 'vulnerable age groups' indicator was constructed by calculating the percentage of an LGA's population made up of the <15 and >65 age group combined. The 'no vehicle homes' indicator is considered as ~~particularly~~ relevant to TCs as it provides information on LGAs that are more susceptible to loss of human life in evacuation situations. Although this risk assessment highly values human life and safety, historically within Australia, TCs have caused very few fatalities in recent decades, and an indicator describing the vulnerability of infrastructure would be preferred. An alternative to 'no vehicle homes' vulnerability indicator could be the proportion of houses that are not constructed to modern wind loading standards. While this potentially useful indicator was not included in this study due to limited data availability, this could be a topic for future work.

Vulnerability indicators are ideally directly linked to their relevant exposed counterparts; however, these human and society-centred vulnerability indicators were chosen to generally relate to selected ~~chosen~~ exposure indicators which can be estimated as populations and the built environment they are surrounded by. Direct infrastructural vulnerability indicators were of interest, such as building code standards to give information on their susceptibility to wind damages, however due to limited data and the multi-hazard approach of this study, a more general approach was taken.

~~The data that was used to create the risk maps are summarised in Appendix 1.~~

~~1.2.~~ 3.2 ~~TC Risk Mapping~~Mapping Process

~~The TC risk mapping process is schematically described in Figure 1. Before risk could be calculated and mapped based on the collected datasets, data was transformed and converted, as described in the diagram. Most processes occurred within ArcGIS Pro software, however, Python scripts were also utilised for some calculations.~~First, acquired indicator data was transformed and converted into the LGA resolution. As raw data came in tabular (a), point (b) and raster (c) formats, different methods for each were used to summarise information when converted to LGA polygons (d) as depicted in Figure 2. Tabular data from the ABS came at an LGA resolution, so data only needed to be linked to an LGA polygon shapefile in ArcGIS Pro. For storm surge point data which spanned across the coastline every 1km, the average 100-yr surge height value was taken, whereas for exposure point data such as hospitals and substations, the count or number of points in each LGA was taken. For the wind raster data which had no null values and gradually changed in value inland, the mean windspeed value was taken per LGA, while with flood and landslide data the sum of non-null values was taken per LGA.

Comment [CD2]: Reviewer: move appendix up here - add columns on data format and resolution

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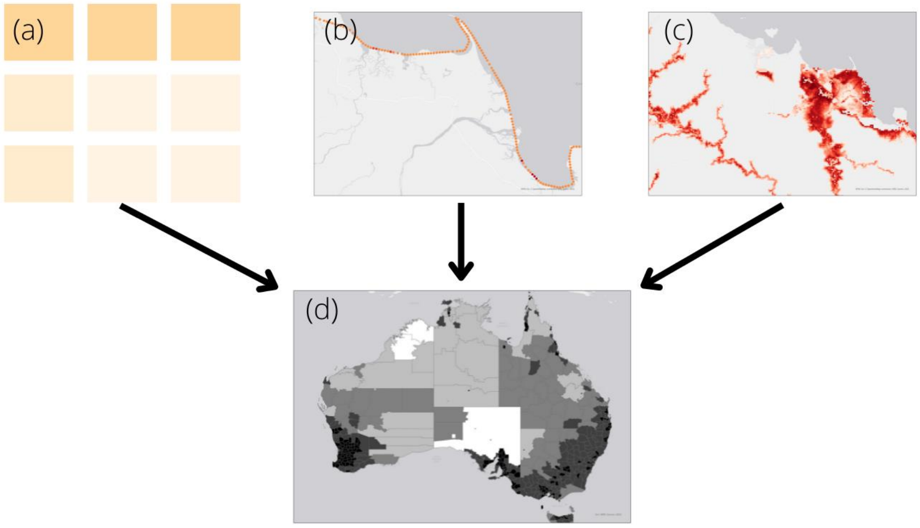

Figure 2. Diagram representing data formats of acquired raw data (tabular (a), point (b), raster (c)) being transformed into a comparable LGA polygon format (d). (Example data is used here, and (d) is not representative of any results)

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Once in a comparable data format, indicator data values were normalised into a 0 to 1 range with decile normalisation against the whole country using Python scripts. Use of different normalisation methods were tested, such as linear normalisation and natural breaks, however decile normalisation was found to best remove the skewing effects of outliers, and is a method commonly used in several ABS indices.

Figure 3 depicts the different tiers or stages of the risk assessment, starting at tier (3) with the indicators. These are the variables that differ in value spatially across Australian LGAs, that were chosen to be representative of TC hazard, exposure, or vulnerability. Three to four indicators were chosen to give a more robust index without diluting the sensitivity of each indicator. From tier (3) to tier (2), or from indicators to indices, different methods were used depending on the index. For exposure, equal weighting was used, while Pareto ranking was used for vulnerability, which is explained in the ~~next~~ sub-section (3.3). With only one indicator or dataset for each hazard of TCs, each hazard was passed through separately, meaning when hazard, exposure, and vulnerability indices were multiplied ~~as outlined in~~using equation 1 to calculate risk (tier (2) to tier (1)), four hazard specific risk layers were produced - TC-induced wind risk, flood risk, surge risk and landslide risk. A quantile classification with five classes (ten for hazard) was used for map symbology.

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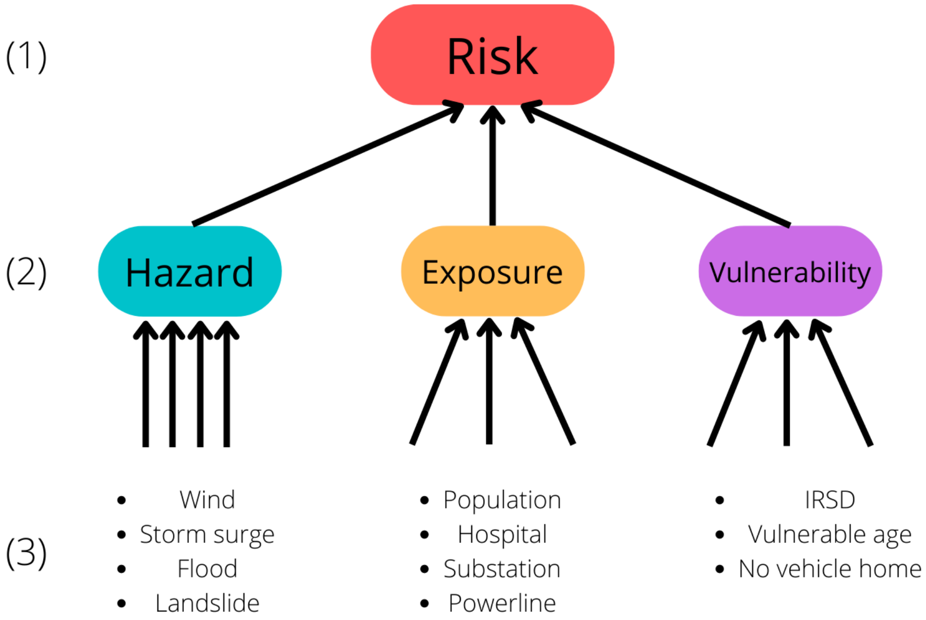

Figure 3. Risk index flowchart from tier (3) indicators to hazard, exposure and vulnerability indices in tier (2), then finally the final risk index (1). Four hazard-specific risk layers are produced, based on the chosen TC-induced hazard indicator chosen.

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~~Transforming raw indicator and hazard data into a workable file format~~

~~(e.g., spatially representing data on a map as shapefiles, preparing raster hazard data)~~

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~~Summarising relevant values for each LGA (e.g., averaging wind hazard cell values,~~

~~counting number of hospitals)~~

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~~Processing summarised values (e.g., converting the number of hospitals to hospitals per sq. km)~~

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~~Normalising values into a 0 to 1 range by ranking each LGA by decile against the rest of the country~~

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~~Creating the exposure index by equal weighting (averaging) decile values~~

~~of the four exposure indicators~~

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~~Creating the vulnerability index by using Pareto Front ranking on the three vulnerability indicators~~

~~Creating the risk index for each hazard by multiplying decile hazard values, the exposure index, and the vulnerability index for each LGA~~

~~Creating map layers for each hazard, each indicator and each index, colour coding~~

~~and using five classes of natural breaks as the symbology classification~~

~~Creating a final TC risk layer by equally weighting the risk of each hazard~~

~~**Figure 1**. TC risk mapping process.~~

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~~2.3.~~ 3.3 Indices Calculation

First, for processing raw indicator data, decile and natural breaks transformations were explored.

Decile ranking in this context compares the values of each LGA to the LGAs in the rest of the country. A value of 0.9 would indicate the LGA has a value larger than 90% of LGAs in Australia, and every 0.1 interval would hold 10% of LGAs. In this way, all indicators can effectively have an impact on resultant indices and risk maps even with the presence of outliers, which will take decile values on either end of the spectrum without causing any skew. Decile ranking is used in indices such as Socio-Economic Indexes for Areas (SEIFA) from which IRSD is a part of, to give relative meaning to the raw scores.

Natural breaks can similarly address the limitations of 0 to 1 normalisation by using optimisation to categorise values and minimise the amount of variance within each category. The number of categories can be increased automatically until a threshold of variance is met (96% in our case, as 97% required more than 20 categories). The breaks or classes chosen depends on and is unique to every distribution or set of data. Additionally, the number of classes is not fixed, which can result in fewer unique values and less value variation between LGAs, which is less informative.

Based on these considerations, decile ranking was chosen as the method of processing raw indicator data. Natural breaks however were used in the presentation of final index and risk maps ~~and colour classes~~ as it is the standard in geographical mapping for choropleth maps (Anchang et al., 2016), providing a quick overview and differentiating ~~values more clearly than a continuous scale.~~clusters of values to easily recognise trends.

Second, index calculations were performed. Equal weighting is commonly used to create index values from a set of indicators, and is used either for simplicity or because there is no supporting evidence to suggest how different indicators should be weighted (Rygel et al., 2006). In the context of ~~TCs in Australia~~natural hazard risk assessment, ~~while~~ past studies have suggested that a weighted framework could improve results ~~(Do and Kuleshov, 2022)~~, but~~it~~ would require more research - such as gathering expert opinion and conducting detailed sensitivity analyses ~~-~~– to weigh chosen indicators (Amadio et al., 2019). One of the limitations of equal weighting is that very high values in one indicator are averaged with other indicators in the index, resulting in a potentially lower value that does not capture the extreme aspect of that LGA. This is particularly a problem for the vulnerability index because a region only needs to be extremely vulnerable in one factor to be considerably more at risk (Rygel et al., 2006).

Pareto ranking, also known as Pareto front optimisation or multi-objective optimisation, was investigated to address some of the limitations of the equal weighting method. Pareto ranking can be used to construct an effective vulnerability index without weighting individual indicators (Huang et al., 2013; Nelson et al., 2020). It involves finding the values along the Pareto front, which are values considered to be non-dominated in all indicator axes and ranking these fronts in order. The process is depicted in Figure 4~~2~~ which shows a step-by-step process of identifying non-dominated data points.

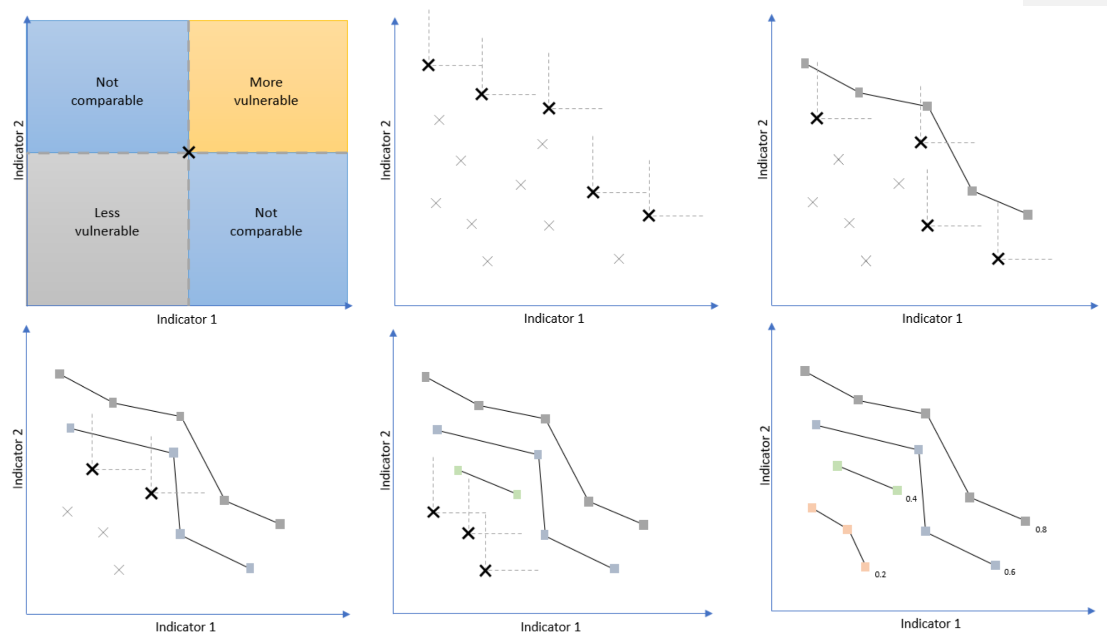

Figure 4~~2~~. Graphic demonstration of Pareto front classification in two dimensions. A non-dominated point is one that has no other points above and to the right of it. The same principle applies when scaled to N number of dimensions. Adapted from Rygel et al. (2016)

First data is plotted along axes representing each component/indicator. Each data point in this study would represent an Australian LGA. Then the first non-dominated front would be identified as the set of points that do not have any LGAs with both a higher value in indicator 1 ~~or~~and indicator 2. This first front would be ranked highest and set aside, with the same methodology being repeatedly used to identify subsequent fronts using the remaining data. In the case of the example in Figure 4~~2~~, with 4 distinct fronts or classes, an index value would be given at even intervals (e.g. 0.2, 0.4, 0.6, and 0.8) with LGAs sharing the same index value as LGAs also in their front.

The Pareto ranking method, therefore, can identify LGAs as vulnerable due to one or two indicator values even if its other indicator values are lower. Although vulnerability benefits from Pareto ranking as the maximum magnitude across all indicators is the defining factor, the exposure index benefits from taking into account all indicators cumulatively assuming the selected indicators are relevant. Thus Pareto ranking was used to calculate the vulnerability index in this study, while equal weighting was chosen for the exposure index.

~~2.~~ 4. Results and Discussion

The TC hazard, exposure, vulnerability, and risk maps are presented and discussed in this section.

~~2.1.~~ 4.1 Exposure

The exposure index was created from equally weighting the four indicators: population density, hospital density, electrical substation density and powerline length density. In Figure 5~~3~~, it can be seen that population density is highest along the eastern coast and surrounding major cities, especially in ~~New South Wales (NSW)~~NSW and ~~Victoria (VIC)~~ VIC. The hospital density indicator shows very similar patterns although there are fewer LGAs with the lowest exposure classification. Substation and powerline indicators both have similar patterns to each other with the highest exposure along south-western ~~Western Australia (WA~~WA~~)~~, southern ~~South Australia (SA)~~ SA, most of VIC, and eastern NSW and ~~Queensland (QLD)~~ QLD. The calculated exposure index in Figure 6~~4~~ maintains the clear trends of highest exposure along the country's eastern coast, and around major cities. ~~Also of note are~~Exceptions include moderate to high ~~relatively high~~ exposure values around the Pilbara region in north-western WA (Karratha, Ashburton, Port Hedland, East Pilbara LGAs) and around Townsville further up the QLD coastline.~~the Mount Isa LGA in western QLD.~~

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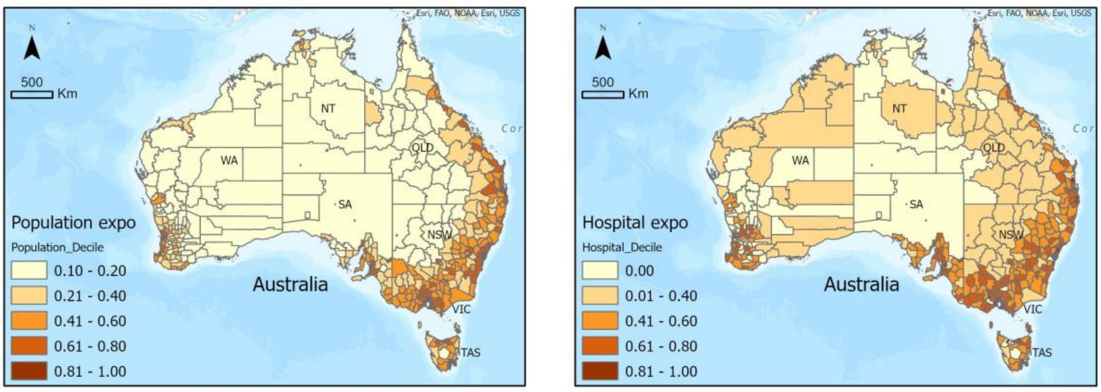

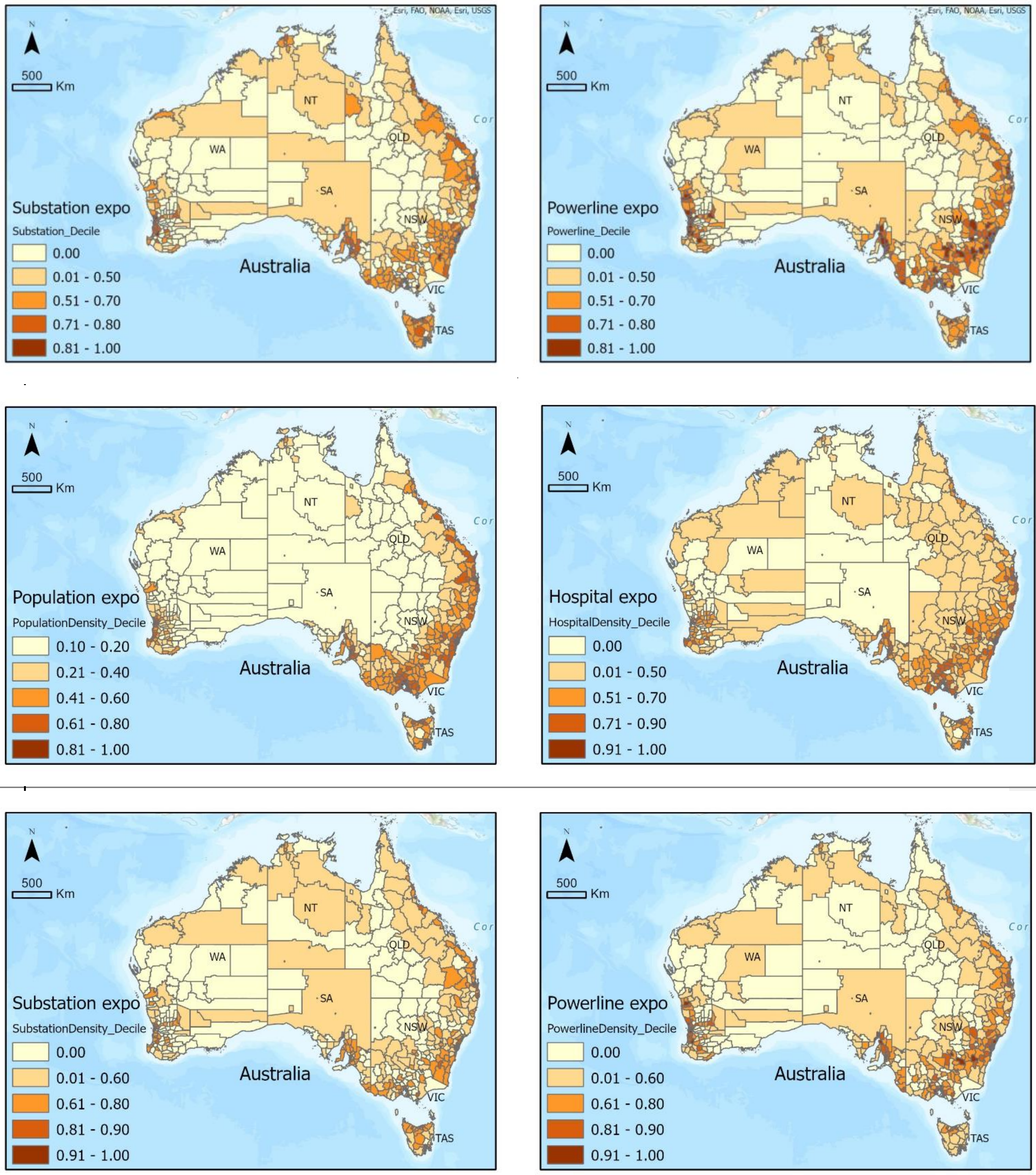

Figure 5~~3~~. Exposure indicator maps of population, hospital, substation, and powerline density.

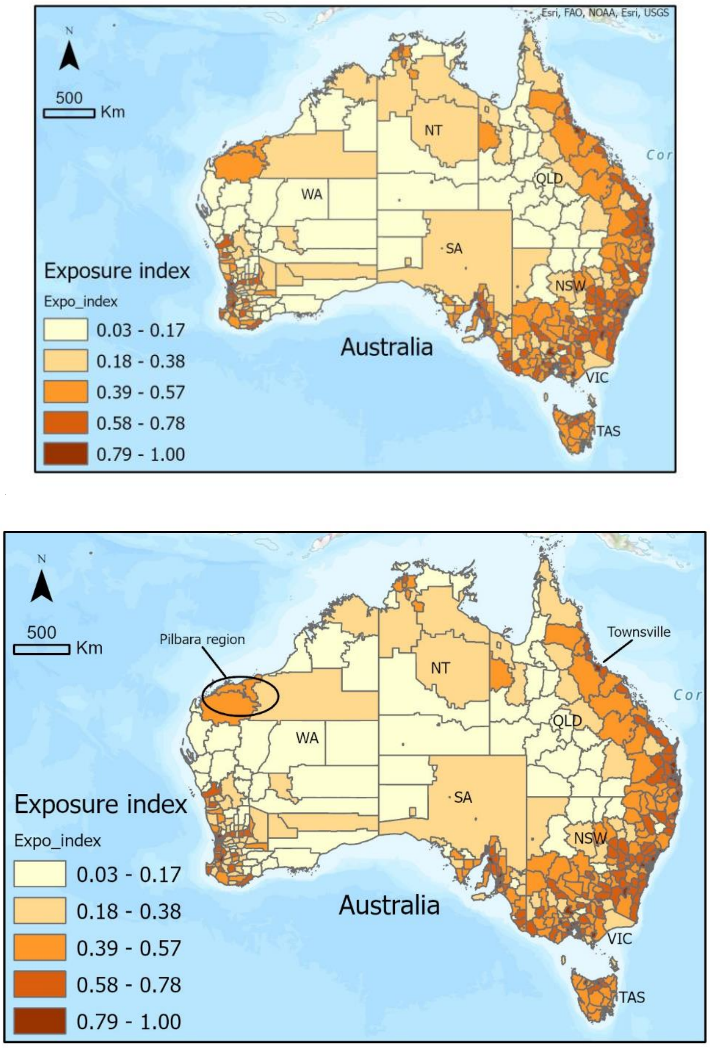

Figure 64. Exposure index map created by equally weighting four exposure indicators.

Exposure maps largely reflect the disproportionate percentage of Australia's population that lives on the coast (Abuodha and Woodroffe, 2006) and near major coastal cities. As infrastructure such as public hospitals and substations are positioned to meet demand, it is also understandable why similar patterns are found amongst chosen indicators.

Aside from these highly populated and built-up coastal regions near major cities, relatively higher exposure index values were identified around the Pilbara and ~~Mount Isa regions~~Townsville regions. The mining industry's presence in regional Australia is most obvious within the Pilbara region of north-west WA, with ~~and the Mount Isa region of north-west QLD. There are a large number of~~many fly-in-fly-out workers for these regions~~, and they~~ which make a significant contribution to the economy. Although none of the chosen indicators were mining industry-related, the population and ~~substation densities~~infrastructure indicators were able to ~~indicate~~detect significant exposure in those areas related to the mining sector. High exposure of Townsville can be explained by a high population making it the largest settlement in North QLD, along with moderate infrastructure indicator values. The city is a popular tourist destination being adjacent to the Great Barrier Reef and national parks, while also hosting large metal refineries.

From the ~~calculated~~ exposure maps, we can see that assets possibly lost in a ~~tropical cyclone~~TC event are highest along the country's eastern coastline as well as surrounding major cities. Thus we would expect the potential for highest risk in these regions if vulnerability and hazard are also high.

~~2.2.~~ 4.2 Vulnerability

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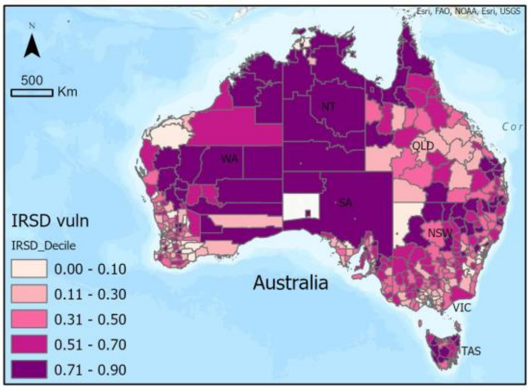
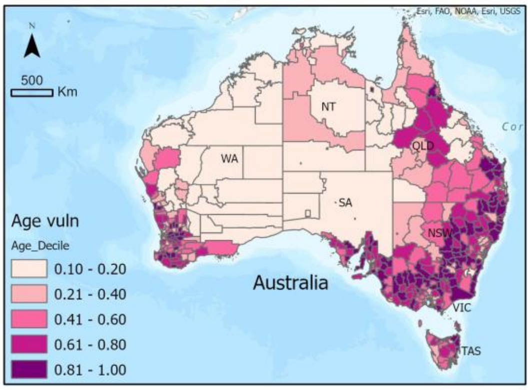
The vulnerability index was created by Pareto ranking the three indicators: IRSD, vulnerable age groups and no vehicle homes.

Figure 7~~5~~ shows that IRSD vulnerability is extremely high across most of central and western Australia, with the highest class values across almost all of NT. Otherwise, vulnerability is considerably lower in the LGAs surrounding the major cities in each state. Conversely, the vulnerable age indicator shows the lowest values across central and western Australia. Although inner cities also show low vulnerable age values, the highest values are found in outer suburban LGAs. For no vehicle homes, central and north-western Australia have the highest vulnerability values, with lower values near and surrounding major cities. The calculated vulnerability index in Figure 8~~6~~ shows low to medium vulnerability values in LGAs surrounding cities, with higher vulnerability regions across NT, northern QLD, and northern NSW to northern VIC.





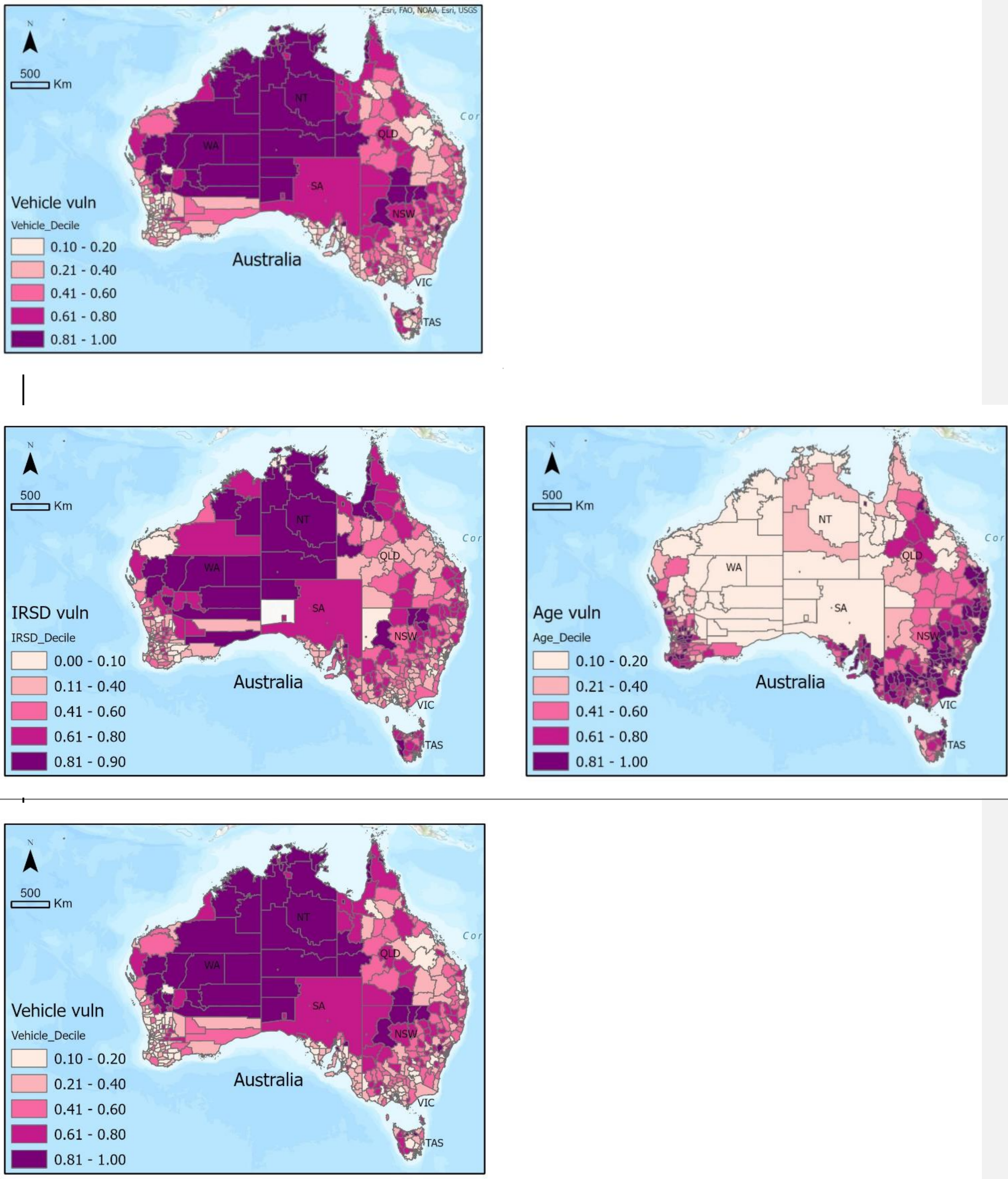


Figure 7~~5~~. Vulnerability indicator maps of IRSD, vulnerable age groups and no vehicle homes.

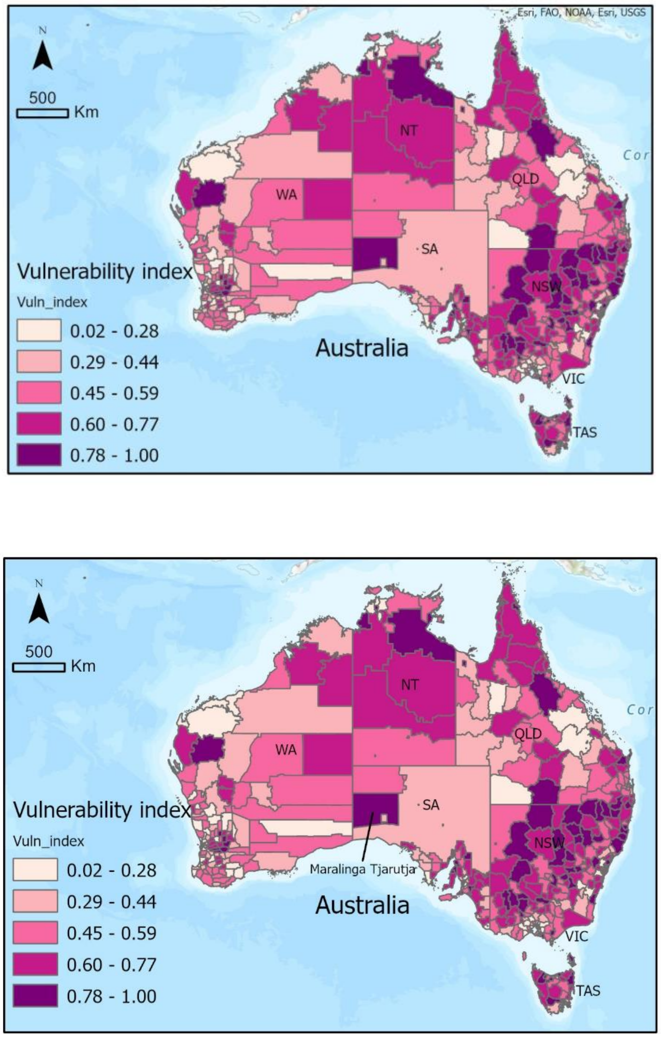


Figure 8~~6~~. Vulnerability index maps calculated by Pareto ranking three vulnerability indicators.

IRSD patterns show lower vulnerability in major cities, as they are most developed and relatively affluent. High vulnerable age group values outside of and surrounding major cities can be explained by the >65 age group retiring and relocating out of urban areas (Vintila, 2001). Of the 16 IRSD input variables, 'NOCAR', was described as the percentage of occupied private dwellings with no car. Although it is not certain whether this variable is the same as the no vehicle homes indicator used in this study from the Number of Motor Vehicles census record, some overlap is to be expected. This means regions with high no vehicle home vulnerability values are likely to have their vulnerability index overestimated. The fact that NOCAR is only one of 16 variables in the IRSD also suggests similarities between the two indicators may be from correlation in other variables instead.

Compared to the exposure index, the transition from patterns in the indicator maps to the vulnerability index are not as clear, as Pareto ranking is used instead of equal weighting. Pareto ranking was used to address situations where a high value in one indicator would be overlooked after being equally weighted with indicators with medium to low values. Instead, it ranks LGAs on the higher end if a single indicator's value causes it to be non-dominated much earlier. However, our analysis showed that having one indicator with the highest classification value does not guarantee a high vulnerability index value. In fact, having two indicators with the highest classification values does not guarantee a high value either as can be seen across central and north WA. This is partly because within each coloured class, there is a range of values, and only the highest values are picked out by Pareto ranking as non-dominated. This suggests the second highest class of values in the vulnerability index (2nd darkest purple) are also important and possibly underestimated.

This idea of there being a lot of competition at the higher value range within indicators is highlighted by the case of the Maralinga Tjarutja LGA in western SA, which is in the highest vulnerability index class. The LGA does not have a recorded IRSD value from the ABS, meaning the region isn't competing for a non-dominated spot on the IRSD axes. This allows the LGA to receive a very high vulnerability index score from only a very high vulnerability value in the no vehicle home indicator alone.

Overall, the vulnerability index shows higher vulnerability and thus predicts higher risk throughout NSW, northern QLD and northern NT.

~~2.3.~~ 4.3 TC Hazards

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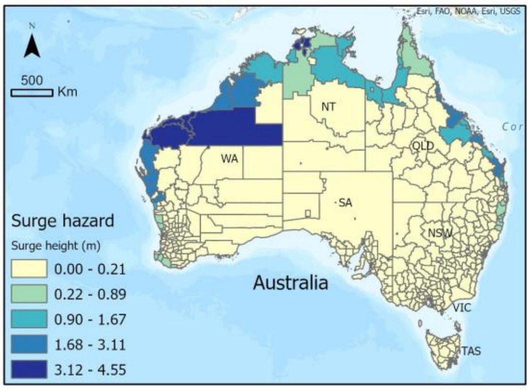
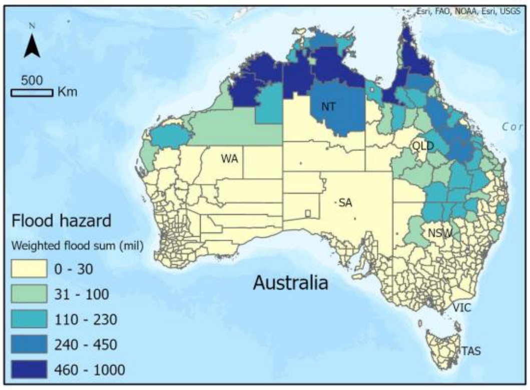
TC h~~H~~azard maps were created from datasets of chosen hazards of storm surge, flooding, wind, and landslides as shown in Figure 9~~7~~. Ten quantile classes (decile) were used to present these TC hazard maps to represent values and display any trends more precisely.





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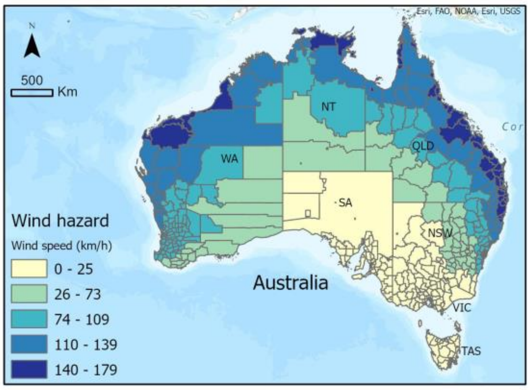
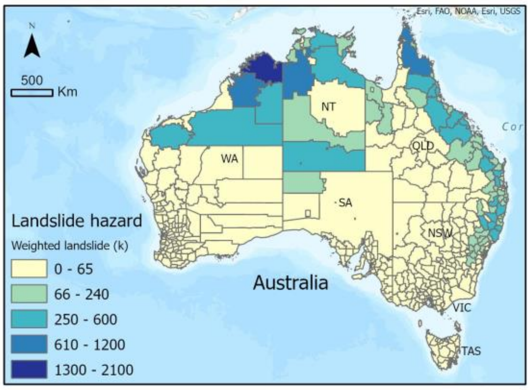
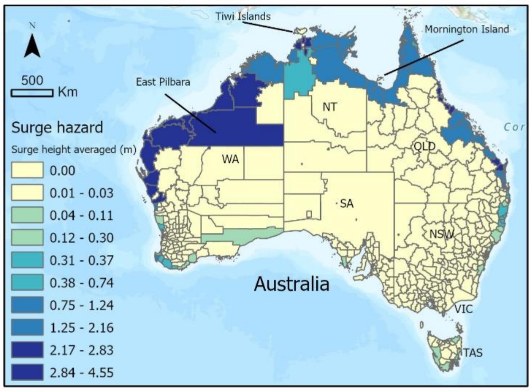
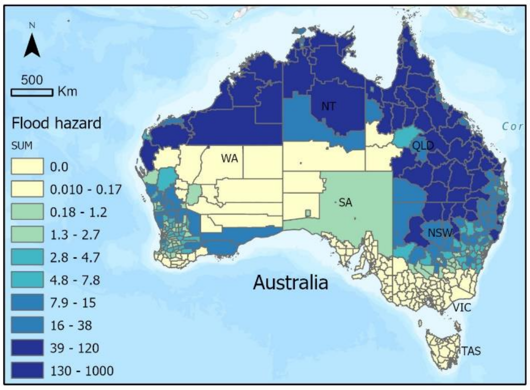

Esri, FAO, NOAA, Esri, USGS
N
500
Km
Wind hazard
Wind speed (km/h)
0 - 25
26 - 73
74 - 109
110 - 139
140 - 179
Australia
WA
NT
QLD
SA
NSW
VIC
TAS


Esri, FAO, NOAA, Esri, USGS
N
500
Km
Landslide hazard
Weighted landslide (k)
0 - 65
66 - 240
250 - 600
610 - 1200
1300 - 2100
Australia
WA
NT
QLD
SA
NSW
VIC
TAS


Tiwi Islands
Mornington Island
East Pilbara
N
500
Km
Surge hazard
Surge height averaged (m)
0.00
0.01 - 0.03
0.04 - 0.11
0.12 - 0.30
0.31 - 0.37
0.38 - 0.74
0.75 - 1.24
1.25 - 2.16
2.17 - 2.83
2.84 - 4.55
Australia
WA
NT
QLD
SA
NSW
VIC
TAS


N
500
Km
Flood hazard
SUM
0.0
0.010 - 0.17
0.18 - 1.2
1.3 - 2.7
2.8 - 4.7
4.8 - 7.8
7.9 - 15
16 - 38
39 - 120
130 - 1000
Australia
WA
NT
QLD
SA
NSW
VIC
TAS

4

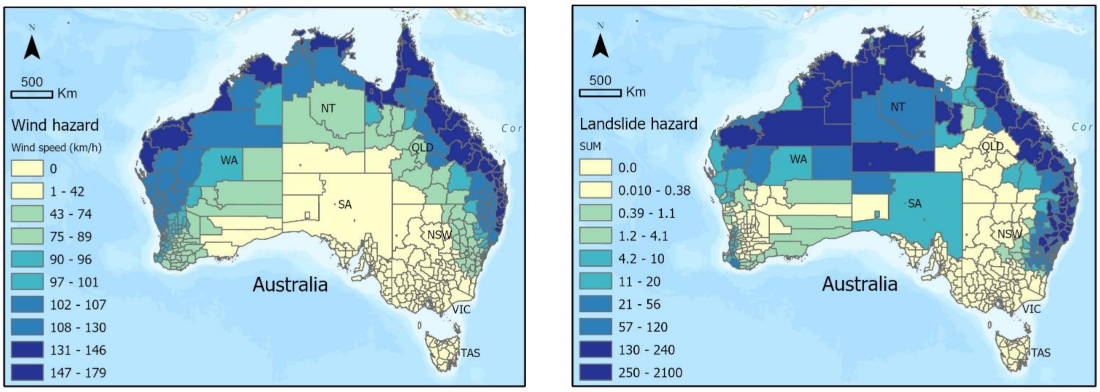


Figure 9~~7~~. Hazard maps of storm surge, flood, wind and landslides associated with Tropical Cyclones.

Surge heights are seen to be highest along a long portion of~~in~~ north-western WA, ~~and~~ surrounding Darwin, and at a few locations along QLD's eastern coastline, having 100-year return period surge heights greater than 2~~3~~m. Surge hazard is otherwise lower around other parts of the country's northern shoreline and has values of 0 in LGAs not bordering the coastline. Flood hazard is shown to have the highest values across northern ~~LGAs~~WA, NT and most of QLD, with ~~medium~~significant values ~~over much of QLD~~reaching into NSW. Wind hazard is more consistent, with TC wind speeds highest in coastal LGAs, with hazard decreasing towards the centre of Australia and further south. Landslide hazard is highest in northern WA and NT along with ~~medium~~ high values throughout ~~throughout NT and along the Great Dividing Range along the eastern coast of the country~~eastern QLD and north eastern NSW.

While it would be expected that the multiple hazards associated with TCs follow the general location TCs more commonly make landfall, there are clear differences between hazard maps in Figure 9~~7~~. This shows how the physical characteristics of each LGA can change the intensity with which different TC hazards impact different regions. For example, flood and landslide hazards have the potential to affect more inland regions while storm surge is only relevant for coastal LGAs, and wind more uniformly decreases south and inland. These results emphasise the importance of considering the multi-hazard nature of TCs and mapping their differing extents.

The storm surge hazard map shows greater than zero values only for coastal LGAs, however, a few LGAs may raise concern. The first is East Pilbara, the large LGA in WA with very high surge values. Although most of the LGA is quite far inland and would not be affected by potential storm surge, the LGA does border the coastline in its northwest corner. Due to input surge datasets having the format of point data dotted every few kilometres along Australia's coastline and chosen methods averaging intersecting surge point data to each LGA polygon, East Pilbara was mapped with very high surge hazard. For a similar reason of input hazard data only dotting the ~~main coastland~~mainland, some island LGAs were left without a surge value and thus mapped with ~~very low~~lowest hazard. For example, Tiwi Islands north of Darwin, and Mornington Island in north-western QLD. Considering their location and the hazard values of neighbouring LGAs, these island LGAs in the country's north potentially have medium to very high hazard values rather than none at all. These cases pose the question of the chosen LGA resolution in this study, with higher resolutions being preferred especially for hazard indicators. The method in this study however applies the same rules and calculations for all LGAs, which allows for a low resource and quick rendition of relative hazard.

Wind hazard trends are to be expected and are consistent with TC genesis and development ~~theory~~ where TCs start to ~~they~~ lose intensity after landfall~~ing~~, having its energy source of warm ocean water cut off. ~~and being cut off energy source while as they penetrate inland, no longer being supported with convection currents from~~ ~~over ocean~~ Additionally, as they move away from the tropics~~too far from the equator~~, TC's storm structure ~~can~~ weakens~~ and collapse, sometimes continuing to exist as an ex-TC storm~~ and they transition into extra-tropical systems with less organised convection and lower wind speeds, although still capable of continuing to ~~to~~ bring~~ing~~ heavy precipitation if the conditions allow. This could partly explain why surge and wind, which rely on high wind speeds, affects less regions strongly south of QLD than flood and landslide hazards which rely on heavy and sustained precipitation.

An important consideration when evaluating flood and landslide hazards is that a cumulative method was used to calculate hazard values from input datasets. Rather than taking averages over each LGA as was done for surge and wind, flood and landslide input datasets were high-resolution raster maps with many null values. Using an averaging methodology would have described an LGA's hazard in proportion to its area, meaning larger LGAs with many flood-prone regions could still have a low flood hazard value. Instead, values were summed, meaning greater than zero hazard values meant a region had some hazard-prone regions, and high hazard values meant they had more regions prone to flooding/landslides regardless of the LGA's size. While this does mean larger LGAs have the potential to reach higher hazard values, this method represents all possible hazards, and therefore risk, rather than underestimating it due to averaging methods.

~~2.4.~~ 4.4 TC Multi-hazard Risk

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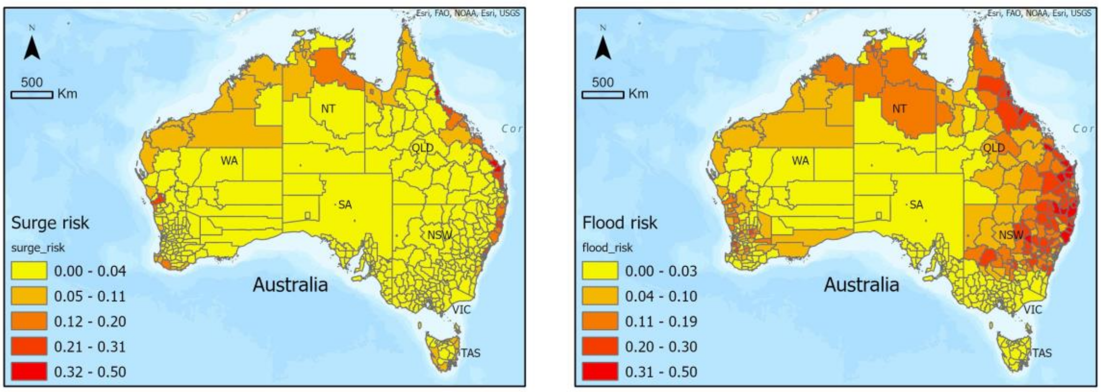
Risk maps were created by multiplying each hazard with the exposure and vulnerability indices. This produced the four hazard-specific risk maps in Figure 10~~8~~, from which a total TC risk map was created by equally weighting them as seen in Figure 11 ~~9~~. A Natural Breaks symbology was used for these risk maps to group similar values and maximise variance between groups for a visually informative map.



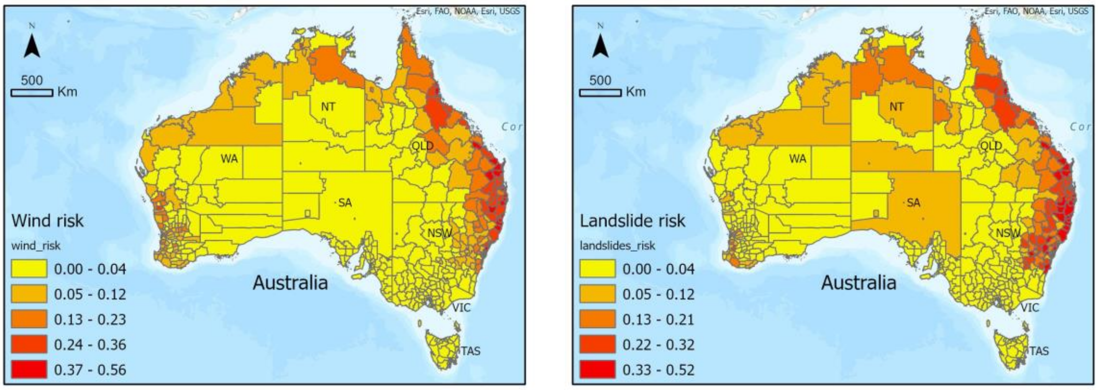


Figure 10~~8~~. Risk maps for each hazard (surge, flood, wind, landslide).

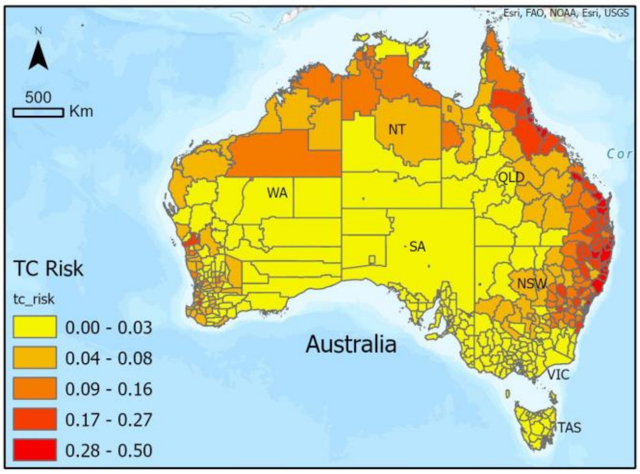


Figure 11~~9~~. Combined multi-hazard risk calculated by equally weighting four hazard-specific risk maps.

Surge risk is considerable along the northern, western, and eastern coasts, with the highest values between Brisbane and Cairns in QLD. Flood risk can be seen to be highest across both NSW and QLD with medium values along the top of NT and WA. Risk to ~~the~~ wind is very uncommon at distances greater than 500 km inland and south of NSW, with the highest wind risk found along with the eastern parts of NSW and QLD. Landslide risk also shows the highest risk in eastern NSW and QLD with medium risk across northern NT. The combined TC risk map displays some of these more prominent patterns from each hazard-specific risk map. For example, eastern NSW and QLD have the highest risk followed by medium risk across northern WA and NT. The risk to TCs is very low inland of the country surrounding SA, as well as south of NSW, in VIC ~~and Tasmania (TAS) states~~ and TAS.

As patterns seen in risk maps can be partially explained by similar patterns found in constituent layers, it is important to compare them to hazard, exposure and vulnerability layers. While an overall

TC risk map is useful for such discussions, hazard-specific risks are important to consider and compare at a local level, for example when LGA councils are planning disaster management strategies or communicating warnings to residents for an incoming TC.

Of note is that although TCs generally form over tropical warm waters and affect regions near the tropics, they intensify away from the equator reaching maximum intensity approximately at 17-18°S of the equator (Kuleshov, 2020), which partially explains why risk is not highest in all northernmost LGAs. Another contributing factor to medium risk values in the country's north is due to there being relatively fewer assets exposed compared to the rest of the country, as shown by the exposure index in Figure 64. Continuing moving further south away from the tropics, TCs are weakening as sea surface temperatures get colder in extra-tropical regions. Hence, substantial reduction of risk is observed in VIC and TAS. Similarly, TCs weaken over land which is why risk is also very low for central Australian LGAs. The lower risk in these states is supported by historical records of TC tracks from 1970-present (Kuleshov, 2020).

~~From the overall TC risk map in Figure 9, QLD and NSW have the most LGAs with very high-risk scores, particularly along the eastern coast. This result can partially be attributed to high hazard values, as well as high exposure index values with many people and infrastructure built up around those regions. Of note is that although TCs generally form over tropical waters and affect regions near the tropics, they intensify away from the equator reaching maximum intensity approximately 17-18°S of the equator (Kuleshov, 2020), which partially explains why risk is not highest in all northernmost LGAs. Another contributing factor to medium risk values in the country's north is due to there being relatively fewer assets exposed compared to the rest of the country, as shown by the exposure index in Figure 4. Continuing moving further south away from the tropics, TCs are weakening as sea surface temperatures get colder in extra-tropical regions. Hence, substantial reduction of risk is observed in VIC and TAS. Similarly, TCs weaken over land which is why risk is also very low for central Australian LGAs. The lower risk in these states is supported by historical records of TC tracks from 1970-present (Kuleshov, 2020).~~The risk maps in Figures 10 and 11 attempt to compare the relative risk of each LGA in Australia by summarising values of relevant hazard, exposure, and vulnerability indicators. Thus, we can investigate the risk in a certain region, and trace it back to its components' trends which should show a similar story. The highest risk regions identified along the eastern half of NSW and QLD in all risk maps (exclusively along the coast for surge risk) represents the dense ~~heavy~~ distribution of populations and infrastructure along Australia's eastern states as seen in exposure maps in Figures 5 and 6. Accompanied by very high flood and landslide values, with wind and storm surge weakening in the southern half of NSW, the eastern strip of Australia stands out to have the highest risk. The influence of vulnerability has a less noticeable trend as it does not uniformly compound in all regions with high hazard and exposure, but can be seen to increase risk particularly in north-central NT, northern QLD and northern NSW.

This holistic approach to assessing risk is helpful in understanding the possible impacts if a TC was ~~were~~ to occur and affect any region in the country. Results have shown that this methodology is effective in visually describing and identifying regions with high risk component values, and hopes to provide relevant risk information to assist disaster management and resilience decision makers.

~~2.5.~~ 4.5 Limitations of Risk Assessment

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One of the limitations of this TC risk assessment of Australian LGAs is that indicators were selected partially because of data availability, and hence may not represent all aspects of hazard, exposure, or vulnerability. For example, within the vulnerability index, indicators that informed a region's preparedness to natural disaster events were not available. While some LGA councils may have informative documents or evacuation plans, it is difficult to determine how well understood they are by residents, and the data is not standardised in the format that can be compared against LGAs across the country. Additionally, in some cases lower resolution global hazard datasets were used because they were available, while higher resolution, Australia-specific datasets are yet to been created or were inaccessible.

Being a risk assessment, subjective indicator choices were made which can shift how results should be interpreted (Aguirre-Ayerbe et al., 2018; Brooks, 2003). For example, chosen exposure indicators identified regions where many lives were exposed alongside physical lifeline infrastructure that contributes to health and utilities (hospitals, powerlines~~electricity~~). These indicators however do not accurately address potential financial losses if businesses and industries were not able to function due to TC damage. As a result, discussion of risk map implications would need to stay human-centric. While just adding more indicators could be identified as a possible solution, the nature of risk and index calculations mean that adding more indicators reduces the importance of each, resulting in a potentially less informative final risk map.

Another limitation is that while each indicator map had patterns identified, the discussion was based on an incomplete understanding of Australian LGAs. Ideally, formal validation of each indicator with local knowledge from people who reside in or manage each LGA would ensure that each contributing input to end risk maps were accurately represented. This would be particularly important for TC hazard data as exposure and vulnerability indicators from the ABS are typically well validated and iterated upon every census. Engagement with indigenous people would also be an essential aspect of validation so that cultural assets and indigenous knowledge are included in the maps.

~~3.~~ 5. **Conclusions**

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The developed novel methodology for multi-hazard TC risk assessment and created maps showed the differences in hazard extent and differing characteristics of each region that made an LGA at risk to TCs. Generally, the highest level for all TC hazards was found along the eastern, northern, and western~~,~~ coasts, with all TC hazards being weakest far inland and in the southern parts of the country. Selected exposure indicators represented human lives as the most important asset at risk, which was found to be highest around major coastal cities in each state, while vulnerability showed more varied spatial trends. Final TC risk maps suggested most at-risk states were QLD and NSW for all TC hazards, particularly in the states' eastern regions followed by medium risk across Northern Territory and north-west of Western Australia~~.~~. As with all risk assessments, the selected indicators should be considered before using resultant maps to inform decisions, and future work includes all-important validation studies.

~~4.~~ 6. **References**

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~~5. Appendix~~

~~**Appendix 1**. Data table for LGA risk analysis. Links are provided for the data sources as well as the year that the dataset was last updated.~~

~~**Indicator**~~	~~**Dataset used**~~	~~**Source**~~	~~**Year**~~
~~**Hazard**~~			
~~Surge hazard~~	~~Point feature layer of Storm surge run-up height, 100yr return period~~	~~GAR Atlas~~	~~2015~~
~~Flood hazard~~	~~Raster Flood depth inundation, 100yr return period~~	~~GAR Atlas~~	~~2015~~
~~Wind hazard~~	~~Raster Cyclone wind, 100yr return period~~	~~Geosciences Australia~~	~~2018~~
~~Landslide hazard~~	~~Raster Global landslides hazard~~	~~ARUP~~	~~2020~~
~~**LGA Exposure**~~			
~~Population density~~	~~Recorded total number of people living in each LGA.~~	~~ABS Census data~~	~~2016~~
~~Public hospital~~	~~Point feature layer of public hospitals around Australia~~	~~ArcGIS Online Dataset~~	~~2019~~
~~Substations~~	~~Point feature layer of power substations around Australia~~	~~Geosciences Australia~~	~~2016~~
~~Powerlines~~	~~Line feature layer of powerlines around Australia~~	~~Geosciences Australia~~	~~2016~~
~~**LGA Vulnerability**~~			
~~IRSD~~	~~Summary statistic for socioeconomic status,~~	~~ABS Census data~~	~~2016~~
~~No vehicle homes~~	~~Percentage of households within each LGA that owns zero vehicles.~~	~~ABS Census data~~	~~2016~~
~~Vulnerable age groups~~	~~Percentage of LGA population that is under 15 or over 65~~	~~ABS Census data~~	~~2016~~
~~**Shape layers**~~			

~~LGA polygon layer~~	~~Shapefile containing the size of each LGA as of 2016~~	~~ABS~~	~~2016~~