Validating a Tailored Disaster Risk Assessment Methodology: Drought Risk Assessment in Local PNG Regions

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Abstract.

Climate change is increasing the frequency and intensity of natural hazards, causing adverse impacts on vulnerable communities. Pacific Small Island Developing States (SIDS) are of particular concern, requiring resilient disaster risk management consisting of two key elements: proactivity and suitability. User-centred Integrated Early Warning Systems (I-EWSs) can inform resilient risk management. However, an EWS is only effectively integrated when all components are functioning adequately. In Pacific SIDS, the risk knowledge component of an I-EWS is underexplored. Risk knowledge is improved through efficient risk assessment. A case study assessing drought risk in PNG provinces was conducted to demonstrate the development and validate the application of a tailored risk assessment methodology. Hazard, vulnerability, and exposure indicators appropriate for monitoring drought in PNG provinces were selected. Risk indices for past years (2014-2020) were calculated and mapped in Geographic Information Systems (GIS). Risk assessment results were validated with a literature investigation of sources presenting information on previous droughts in PNG. The risk assessment indicated a strong drought event in 2015-2016, and a moderate event in 2019-2020. The literature corroborated this, confirming the validity of the risk assessment methodology. The methodology and results can be used to inform improved disaster risk management in PNG, by advising decision-makers of their risk and policymakers on which provinces are of priority for resource allocation. The methodology can also be used to enhance the risk knowledge component of a user-centred I-EWS and guide the implementation of such a system for drought in PNG and other Pacific SIDS.

Keywords: Climate Risk; Disaster Risk Assessment; Resilient Management; Early Warning System; Small Island Developing States; Papua New Guinea

1 Introduction

1.1 Disaster risk reduction and resilient risk management of natural hazard events

Increased intensity and frequency of natural hazards and disaster events resultant of a changing global climate are already seen to have destructive impacts on the world's most vulnerable communities (Mercer, 2010). Future effective climate adaptation and disaster risk reduction (DRR) is vital for the resilience of vulnerable communities. Small island developing states (SIDS) in the Pacific include some of the most hazard-vulnerable communities in the world. Pacific SIDS are disaster-prone and have low capacity to cope with resultant impacts, due to limited resource availability, including water and food insecurity, and reactive management practices. For example, a prolonged drought event across the Pacific in 2010-2011 affected multiple SIDS, including Samoa, Tokelau, Tonga, and Tuvalu (Kuleshov et al., 2014). Impacts were severe in all affected countries, but most extreme in Tuvalu where a water crisis occurred. This prompted a state of emergency declaration by The Government of Tuvalu and resulted in the rationing of freshwater in households. Due to the highly hazard-vulnerable nature of Pacific SIDS, they are of priority for increasing resilient disaster risk management efforts to achieve efficient DRR.

Resilient disaster risk management consists of two key elements: proactivity and suitability. In this instance, proactivity is characterised by controlling a disaster risk situation prior to the occurrence of a natural hazard event, rather than responding to disaster after it has reached a crisis level. Suitability is defined as the quality of disaster management appropriateness for the independent implementation of management at a localised level in vulnerable places. Thus, when seeking to increase disaster resilience in SIDS, the proactivity and suitability of localised disaster risk management is of critical focus. DRR policies and resilient management strategies are becoming increasingly established within the international development community, however there remains a need to effectively manage climate change at a localised level in SIDS through targeted DRR and climate adaptation strategies to ensure community resilience (Mercer, 2010).

1.2 User-centred Integrated-Early Warning Systems

User-centred Integrated Early Warning Systems (I-EWS) are increasingly recognised as key to informing proactive and suitable disaster risk management decisions in local vulnerable areas to increase disaster resilience. The United Nations Office for DRR defines an EWS as "The set of capacities needed to generate and disseminate timely and meaningful warning information to enable individuals, communities and organisations threatened by a hazard to prepare and to act appropriately and in sufficient time to reduce the possibility of harm or loss" (United Nations International Strategy for Disaster Reduction (Unisdr), 2006). However, for an I-EWS to significantly contribute to enhanced disaster risk management at local disaster resilience, it must be effective.

An effective user-centred I-EWS consists of four inter-connected components including Risk Knowledge, Warning Service, Communication and Dissemination, and Response Capability (De León et al., 2007). Each component is key to the efficiency of the overall I-EWS, and if one component is lacking, the entire system would not succeed in efficiently informing disaster risk management. The first component, risk knowledge, considers the patterns and trends in hazards and

65 vulnerabilities that are present from which risks arise (De León et al., 2007). Key tools recognised as useful to exploring the risk knowledge component include risk assessments and risk mapping. These tools improve hazard, vulnerability, exposure, and overall risk knowledge, set priorities in I-EWS needs, and guide response preparedness and risk management (Rahmati et al., 2020; Aitkenhead et al., 2021). The risk knowledge component is of particular interest currently as past I-EWS investigations have only explored risk knowledge at a broad, rather than local level, while mainly focusing on the warning

70 service component.

As part of the Climate Risk and Early Warning Systems (CREWS) international initiative, the Australian Bureau of Meteorology is developing a user-centred I-EWS for drought in PNG, that utilises the World Meteorological Organization's (WMO) Space-based Weather and Climate Extremes Monitoring (SWCEM) products (Kuleshov et al., 2019) and delivers

75 warnings and relevant drought hazard information to end-users (Kuleshov et al., 2020). While the warning service component has already been developed (Bhardwaj et al., 2021a,b), the risk knowledge, communication and dissemination, and response capability components of I-EWSs require further investigation. The implementation of all four components of a user-centred I-EWS to inform proactive and suitable risk management in local communities must be investigated at a more targeted level to ensure resilience of vulnerable communities in the future (Pulwarty and Sivakumar, 2014). Future

80 consideration for the implementation of the risk knowledge component on a localised level is firstly required to begin informing maximum efficiency in I-EWSs for SIDSs.

1.3 Investigating natural hazard risk knowledge at a localised level

A common technique used in global studies investigating disaster risk knowledge, which has the potential for application to investigating risk knowledge in SIDSs is disaster risk assessment. Disaster risk assessments analyse the risk of natural

85 hazards in a particular area. Disaster risk is defined as the probability of harmful consequences, or expected losses resulting from interactions between disaster hazard (the possible future occurrence of natural hazard events); disaster exposure (the total population, its livelihoods and assets in an area in which natural hazard events may occur); and disaster vulnerability (the tendency of exposed factors to suffer negative impacts when natural hazard events occur) (Sharafi et al., 2020). Risk assessments are vital to indicating the most at-risk places to natural hazards in a given area that are of priority for improved

90 risk management.

The vitality of such assessments is demonstrated by Rahmati et al. (2020) in their study of drought risk in a vulnerable area of south-east Queensland, Australia which provided recommendations detailing areas within which drought resilience could

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be improved. The drought risk index developed as part of the drought risk assessment by Rahmati et al. (2020) also had
95 implications for utilising integrated Geographic Information System (GIS)-based mapping techniques to accurately map and
visualise drought risk levels of particular places to better inform drought relief preparedness strategies in those areas.

Integrated GIS-based mapping techniques for risk assessment include three key components: data integration into GIS, risk
assessment tasks, and consideration of risk decision-making (Chen et al., 2003). The first component, data integration into
100 GIS, consists of data collection and assimilation onto a GIS platform and data transformation and standardisation. Risk
assessment tasks are then performed on the GIS platform, including individual hazard, vulnerability, and exposure
assessments with accompanying mathematic calculations (Hagenlocher et al., 2019). The consideration of risk decision-
making is incorporated through efficient data visualization on GIS risk maps and appropriate dissemination of such products
to decision-makers.

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Although disaster risk assessments have been conducted for a variety of natural hazards in numerous countries throughout
the world, there has been minimal risk assessment conducted for natural hazards in SIDSs. Out of the disaster risk
assessments that have been conducted in SIDS, they have been conducted on a broader level rather than local area or
community level (Hagenlocher et al., 2019). For risk assessments to effectively inform proactive and suitable disaster risk
110 management in local areas and vulnerable communities, they must be tailored to the area of study (e.g. the specific country,
states or provinces, and/or local communities being investigated) (Wilhelmi and Wilhite, 2002). Tailored risk assessments
would use specific hazard, vulnerability, and exposure indicators appropriate for monitoring hazard risk of the hazard under
investigation, in the study area. Additionally, those risk assessments that have been conducted in SIDS have not utilised the
integrated GIS methodology recommended by Rahmati et al. (2020), Hagenlocher et al. (2019), and Chen et al. (2003).
115 Therefore, there is room for future investigation of risk knowledge in SIDSs to implement a tailored risk assessment with
specific hazard, vulnerability and exposure indicators, and map indices produced by such assessment using integrated GIS
methodology.

1.4. Validating disaster risk assessments to ensure accuracy and usability of results

In addition to past disaster risk assessments not utilising the most efficient methodology, they also commonly lack adequate
120 validation (Asare-Kyei et al., 2017). In a review of past disaster risk assessment methodology, Hagenlocher et al. (2019)
state that comprehensive validation "has proven to provide relevant information on the reliability, validity, and
methodological robustness of risk assessments and their outcomes. However, its application in the field of risk assessment
remains largely underdeveloped." Molinari et al. (2019) explain further that risk assessment validation is crucial; results can
be used to inform large investments and allocation of resources, as well as other important risk management decisions, so
125 results need to be credible. Among the few studies seeking to validate a risk assessment methodology, various validation
techniques have emerged.

Validation through result comparison with historical data has been used in several studies, however the preciseness of this method has been criticised. To validate the agricultural drought risk assessment methodology which they developed for use in Nebraska (U.S), Wu and Wilhite (2004) estimated the probability of correct risk classification with independent, historical crop data. This historical data was then compared to the risk assessment results to verify accuracy. Similarly, Fekete (2019) validated the results of a flood vulnerability assessment through comparison with social data from the time period assessed. However, Fekete (2019) explains that the absence of globally accepted benchmarks for social, exposure and hazard data explicitly focused on revealing disaster risk, leaves too much to author interpretation when using this validation method. Molinari et al. (2019) also critics the validation through comparison with historical data technique, stating that there is "the need of higher quality data to perform validation and of benchmark solutions to be followed in different contexts, along with a greater involvement of end-users".

An alternative technique, incorporating the views of end-users as a 'ground-truth' source, called participatory research is becoming increasingly utilised to validate drought monitoring outcomes, including risk assessment results. This technique includes collaboration with stakeholders in a capacity building process as well as consideration of local peoples and expert observations into knowledge systems (Mckenna and Yakam, 2021; Fragaszy et al., 2020). For example, Fragaszy et al. (2020) used participatory validation by conducting interviews, focus groups and workshops to assess the extent of drought impacts experienced during the study period, to verify the results of a drought assessment conducted in the Middle East and North Africa.

Although participatory research is a promising validation methodology, past investigations using this method have used an additional 'ground-truth' source to strengthen validation adequacy. To verify results of remotely sensed drought risk monitoring in Morocco, Bijaber (2018) compared results to historical on the ground precipitation and crop production data at national scale as well as the views of experts regarding what was experienced on the ground during the investigated period. Asare-Kyei et al. (2017) employed an analogous technique to validate flood risk assessment results for the urban area of Shanwei City in People's Republic of China. Records of impacts and results of household interviews were intended to be used as ground-truth sources for impact data which the risk assessment results could be compared to for verification. However, Asare-Kyei et al. (2017) found no systematically documented records of the impacts, and thus had to rely on local's recounts which were focused on the high intensity impacts, and often forgetful of small impacts.

In Pacific SIDS, data availability is scare, thus validation through comparison with historical independent data is unlikely to be credible. Overall, a strengthened validation methodology using multiple ground-truth sources seems most promising for future study regarding the verification of disaster risk assessments.

1.5 Disaster risk assessment for PNG

To continue upon past research regarding integrated GIS-based risk mapping (Rahmati et al., 2020) and I-EWS development (Bhardwaj et al., 2021a), PNG is deemed an appropriate country in which to investigate the risk knowledge component of an I-EWS through disaster risk assessment and mapping. PNG is one of Pacific SIDS, it is vulnerable to climate extremes and disaster events and is predicted to be increasingly affected by impacts from tropical cyclones, floods, and drought in the future. The El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) are key drivers of climate variability and resultant hazard events in PNG, and other Pacific SIDS.

In Pacific SIDS, ENSO alters the distribution of precipitation, often causing natural hazard events (Horton et al., 2021). ENSO has two key phases: El Niño (warm phase of ENSO) and La Niña (cold phase of ENSO). La Niña-associated prolonged rainfall has contributed to floods, whilst El Niño-associated prolonged aridity has contributed to droughts in PNG (Smith et al., 2013). Historically, the 1997-1998 El Niño contributed to severe drought in PNG causing immense loss of life, destruction of crops, and forest fires subsequently causing regional pollution problems (Nicholls, 2001). However, different regions of PNG experience varying climactic affects from El Niño and La Niña (Figure 1). For example, a moderate La Niña event which occurred in PNG during 2011-2012 resulted in drought conditions in several PNG provinces, particularly Milne Bay Province.

The effects of ENSO can be influenced by the IOD to further weaken or strengthen these trends in rainfall variability (Bhardwaj et al., 2021b). Defined as consistent changes in sea surface temperature variability across the tropical western and eastern Indian Ocean, the IOD can be negative, positive, or neutral, with each phase interacting with ENSO impacts differently (Bhardwaj et al., 2021b). The impacts of interactive IOD and ENSO phases experienced in PNG are shown in Figure 2.

PNG has a lack of coping capacity for managing the risks posed by the natural hazard events which occur across the country (Kuleshov et al., 2020). Particularly, drought poses an immense concern as it historically has disastrous impacts on PNG communities but has not been extensively investigated compared to other hazards like tropical cyclones and floods. Considering the restricted knowledge of drought risk in the context of PNG, and the critical threat which it poses to communities, drought is an appropriate hazard to investigate in terms of assessing disaster risk to local areas in PNG.

Generally, drought can be described as an extended dry period resulting from rainfall deficiency. However, drought has many definitions for its various types: meteorological (when climactic factors result in dry conditions within an area), hydrological (when water shortages occur after a period of meteorological drought), agricultural (when agricultural productivity is inhibited and crops are affected by meteorological and hydrological drought), and socioeconomic (when dry

conditions restrict the supply and demand of commodities) (Wilhite et al., 2014). As drought impacts all major sectors (agriculture, economy, social, health, etc.), a drought risk assessment must not only use indicators tailored for monitoring

195 drought in PNG, but also use a variety of sectoral indicators to encompass the overall drought risk to a local area. Remote communities in PNG continue to have limited resources and capacity to effectively manage such a variety of sectoral impacts. Local areas, for example individual provinces, in PNG must be able to self-initiate strategies that are effective and appropriate to them. In this context, I-EWS and risk assessment informed community/provincial-scale DRR is an increasingly important focus for PNG (Webb, 2020).

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This study will expand on previous research with an aim to address the risk knowledge components of a user-centred I-EWS for informing bottom-up resilient management on the local area scale in PNG. This research seeks to build capacity for the natural hazard monitoring through an I-EWS in PNG, as well as demonstrate the potential for tailored risk assessments to accurately inform on drought risk levels before, during and after a hazard event and thus contribute to more resilient disaster

205 risk management in local SIDS areas. The study intends to use the most effective risk assessment methodology recommended by Rahmati et al. (2020), Hagenlocher et al. (2019), Giardino et al. (2018) and Bhardwaj et al. (2021a) (GIS integrated technique and space-based weather and climate extremes observations) to conduct a unique and tailored risk assessment and mapping of drought in PNG, and seeks to perform a comprehensive validation of the risk assessment results using literature records as a 'ground-truth' source.

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2. Data and Methodology

2.1 Study Area: PNG

PNG has a population of approximately 8.8 million across its mainland and six hundred islands, which have a total land area of 452,860 km^2. The country consists of four major regions, within which the 22 provinces of PNG are divided (Figure 3).

215 The four major PNG regions and their provinces are as follows:

-Highlands Region: Chimbu (Simbu), Eastern Highlands, Enga, Hela, Jiwaka, Southern Highlands, and Western Highlands.

-New Guinea Islands Region: Bougainville (North Solomons), East New Britain, Manus, New Ireland, and West New Britain.

-Momase Region: East Sepik, Madang, Morobe, and Sandaun (West Sepik).

220 -Southern Region: Central, Gulf, Milne Bay, Oro (Northern), and Western (Fly River).

PNG is largely mountainous, and much of it is covered with tropical rainforest. The climate of PNG can be described as tropical throughout, however each region of PNG experiences differences in seasonal climactic factors (Figure 3) (Bhardwaj et al., 2021b). PNG climate also varies between years, with a dominant driver being ENSO (Figure 1).

PNG society consists of traditional village-based life, dependent on subsistence and small cash-crop agriculture, as well as
modern urban life in the main cities.

Economic performance in PNG has historically been based on international prices for exports (including for agriculture),
fiscal policies and construction activity. As of 2015, over 2 million Papua New Guineans are poor and/or face hardship,
particularly those based in rural areas (Pacific Islands Forum Secretariat, 2015). Agricultural occupation is consistently
important for local livelihoods, with approximately 80-85% of the rural population directly deriving their livelihood from
farming (Pacific Islands Forum Secretariat, 2015).

2.2 Study Design

The methodology for this study was three-part:

1. Selection of tailored hazard, vulnerability and exposure indicators appropriate for monitoring drought risk in PNG
    provinces.
2. Calculation and GIS mapping of hazard, vulnerability, exposure, and risk indices for historical years (2014-2020) to
    determine the occurrence of drought events in PNG in the past.
3. Validation of drought risk assessment accuracy through a comparison of the drought risk index results with
    literature detailing severity of drought conditions and impacts experienced on the ground at the time of each drought
    event indicated by the risk assessment.

2.2.1 Methodology: Part 1

Tailored risk indicators were selected for monitoring drought in PNG as the development of a region-specific drought risk
index is the key to accurate drought risk calculation and mapping (Santos et al., 2014). All types of droughts were
considered when selecting indicators, as well as all major sectors across PNG provinces. This was done to provide a holistic
risk index for PNG provinces, as each type of drought is known to impact PNG communities (Kuleshov et al., 2020), with
each major sector experiencing the effects (Bhardwaj et al., 2021b).

Hazard, vulnerability, and exposure indicators most applicable to drought risk assessment in the 22 provinces of PNG were
determined by integrating information regarding the socio-economic, geographic, and climactic characteristics of PNG
provinces and analysis of indicator selection used in earlier studies of characteristically similar areas (Refer to Appendix A
for a detailed table describing the reasons for selection of each indicator). PNG National Weather Service advice was also
sought to approve indicator selection. Additionally, hazard indicators were assessed against recommendations made by
WMO in their Handbook of Drought Indicators and Indices (Svoboda and Fuchs, 2016). Note, data was only available for
certain indicators as data availability is poor in PNG, thus indicators which could have been more appropriate for use in
hindsight had to be omitted. The most applicable and representative indicators were selected from what was available.

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The indicators that were selected for use in assessing PNG provincial drought risk are shown in Table 1. Refer to Appendix B for a list of indicator data sources. It is key to note that space-based monitoring products were used when gathering data for hazard index calculations to ensure accuracy[1].

2.2.2 Methodology: Part 2

260   Historical and current data detailing hazard, vulnerability, and exposure conditions in each of the 22 PNG provinces for each year within the 2014-2020 period in PNG, was used to develop a risk index for each year in this historic period to see if it would have indicated high disaster risk and whether it is suspected that a drought event(s) actually occurred during this period. The historical assessment was conducted from 2014 onwards due to no data availability for space-based Vegetation Health Index (VHI) before 2014. Integrated-GIS methodology for mapping risk in each study region was used to display risk

265   levels for the overall years 2014-2020. It was then determined whether a drought event was suspected as occurring across PNG in each of the years assessed.

A nationwide drought event was suspected when the majority of provinces were in severe to extreme drought risk conditions and was not suspected when the majority of provinces were in mild to moderate drought risk conditions. This is deemed a fair assumption since in past drought events, when only certain provinces in PNG experienced drought conditions and direct

270   impacts, other provinces encountered indirect impacts and PNG as a nation was adversely affected. For example, during the 1997-1998 nationwide drought event in PNG, dire social, health and economic effects were felt across the entire country (Kanua et al., 2016). Resources of provinces in non-dry conditions were pressured with PNG villagers from drought-affected provinces travelling to areas in non-drought conditions or to relatives living in urban areas seeking familial help and support (Allen and Bourke, 2009). Additionally, a major mine was closed in response to the dry conditions in Western Province,

275   impacting the national economy (Kanua et al., 2016).

The years suspected of experiencing a nationwide drought event were recorded; this record was used in the validation of risk assessment results against literature review results. Risk levels were also determined for the months of November, and December in 2014, January to December of 2015 and November and December in 2016 to demonstrate the transition into

280   and out of drought during any strong drought event indicated by the risk assessment.

Thresholds were applied prior to index calculations and mapping to determine the variance of indicator data between each of the PNG provinces. Thresholds suitable for PNG drought risk indices were adapted from earlier studies in similar areas to

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[1] There is a commonly recognised need to increase the utilisation of monitoring of climate extremes from space. Institutions like the WMO Regional Climate Centres observe weather and climate extremes to produce warnings for climate monitoring including the generation of space-based monitoring products.

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ensure accuracy (Dayal et al., 2018; Frischen et al., 2020b). Once indicator variance was confirmed, raw data was uploaded
285 to ArcGIS Pro.

To calculate the hazard index, data was first reclassified by a linear function on a 1-10 scale and then standardised using
fuzzy logic in ArcGIS Pro (Environmental Systems Research Institute (Esri) Inc., 2019). Data for the vulnerability and
exposure indices was also standardised using *fuzzy* logic. Prior to the performance of the *fuzzy* function, *fuzzy* membership
290 classes were assigned to each indicator, describing the relationship between it and drought risk as recommended in Rahmati
et al. (2020) and Aitkenhead et al. (2021). Two classes of *fuzzy* membership were assigned in this study: *fuzzy small*[2] and
fuzzy large[3]. *Fuzzy* values scaled between 0-1 based on the possibility of the indicator data contributing to drought risk,
where 0 was assigned to values unlikely to contribute to drought risk, and 1 was assigned to values most likely to contribute.
The default midpoint was not used when performing the fuzzy function; the midpoint used for each indicator was based on
295 the mean value in the historical records for indicator data. This ensured that the data was standardised on both a spatial and
temporal scale.

The indicator fuzzy values for each province were mapped in ArcGIS Pro[4]. Fuzzy values of each indicator were used to
calculate hazard, vulnerability, and exposure indices. Numerical weights were assigned to each indicator contributing to the
300 hazard, vulnerability and exposure indices based on an expert weighting scheme informed by past studies and advice from
the PNG National Weather Service (Appendix C). The hazard, vulnerability and exposure indices were calculated using
equations (1), (2) and (3), respectively for each province in the years and months under investigation.

$$HI = \sum_{i=1}^{n}(w_i * x_i') \qquad\qquad (1),$$

$$VI = \sum_{i=1}^{n}(w_i * x_i') \qquad\qquad (2),$$

305 $$EI = \sum_{i=1}^{n}(w_i * x_i') \qquad\qquad (3),$$

where HI is the Hazard Index, VI is the Vulnerability Index, EI is the Exposure Index, n is the number of Hazard,
Vulnerability or Exposure Indicators, x_i' refers to the standardised indicators and w_i refers to the respective indicator weight.

Once the vulnerability, hazard and exposure indices were calculated, spatial maps of the area covering the 22 provinces of
310 PNG, representing vulnerability, exposure, and hazard per unit area, were produced. The final drought risk index value for
each PNG province was determined through the integration of the drought vulnerability, hazard and exposure index maps
using the *Fuzzy Gamma Overlay* function (using a gamma of 0.75) in ArcGIS Pro. A final drought risk map was then

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[2]*Fuzzy small*: a transformation function used when smaller input values are most likely to influence drought risk.

[3]*Fuzzy large*: a transformation function used when larger input values are most likely to influence drought risk.

[4]The base map used for all mapping in this study was gathered from the open-sourced platform, GISMap.

generated. The extent of drought vulnerability, hazard, exposure, and risk displayed on the respective maps was classified into four levels: mild, moderate, severe, and extreme. These classifications are commonly used in drought risk assessments

315 (Dayal et al., 2018; Frischen et al., 2020a). This process was repeated to calculate a drought risk index for each year and month under investigation.

2.2.3 Methodology: Part 3

Risk level accuracy was validated through comparison with documented records of observed impacts during the study period as a ground-truth source. Eight reputable literature sources detailing drought conditions around the time of each event

320 indicated by the risk assessment (2015-2016 and 2019-2020) were analysed to determine the ground-truth of the drought event severity and impact. As two drought events were investigated, and eight sources were assessed for each event, a total of 16 sources were assessed overall (2015-2016 (Chua et al., 2020; Gwatirisa et al., 2017; Burivalova et al., 2018; Jacka, 2020; Varotsos et al., 2018; Kuleshov et al., 2020; Schmidt et al., 2021; Rimes and Papua New Guinea National Weather Service, 2017) and 2019-2020 (Johnson et al., 2019; Food and Agriculture Organisation of the United Nations, 2021; Null,

325 2021; Mckenna and Yakam, 2021; Food Security Cluster et al., 2021; 2019; Papua New Guinea National Weather Service, 2020; Bang and Crimp, 2019)). Three severity levels were identified as being commonly implied in sources: mild, moderate, and severe to extreme. The level most clearly aligned with the details provided by each source was recorded. Additionally, any mention of specific provinces experiencing impacts was recorded.

330 The records in the literature were not extensive for the 2019-2020 drought event in PNG. An array of records was available for the 2016-2020 drought event, but only a few were available for the 2019-2020 event. This may have been due to the 2019-2020 event being so recent, meaning that investigations of the event may still be ongoing and/or peer reviewed literature not being published as of when this research was conducted. To account for the limited availability of literature records for the 2019-2020 drought and to make the comparison with literature equal for both drought events assessed, an

335 equal number of sources were selected for the analysis for each event (eight each). The small number of sources investigated for each drought event was statistically analyzed; a two-tailed p-value was used to determine significance in the statistical tests as a two-tailed p-value accounts for smaller sample sizes and tests for the possibility of positive or negative differences in the samples.

340 Statistical analyses were conducted to determine if there were significant differences between the drought risk level indicated by the risk assessment and the risk level indicated by the literature for each PNG province for each of the drought years under investigation (2015-16 and 2019-20)[5]. An F-test was firstly conducted to determine whether there were equal variances between the levels displayed in the risk assessment and the levels expressed in the literature for the 2015-2016

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[5] Statistical analyses were performed in Microsoft Excel.

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drought event. The F-value (test statistic), degrees of freedom and the two-tailed p-value indicating the level of marginal
345   significance within the test, were recorded. A Student's t-test (assuming equal or unequal variances depending on F-test
results) was then conducted to determine the significance of difference of the drought risk levels indicated by the assessment
and the levels indicated in literature for each province. The t-value (test statistic), degrees of freedom and the two-tailed p-
value were recorded. This process was repeated for the 2019-2020 drought event results. T-test assumptions were checked
by plotting the data distribution on boxplots. All assumptions were met, thus the aforementioned tests proceeded. All
350   statistical tests used $\alpha = 0.05$.

3. Results

The 2014, 2015 and 2016 drought risk assessments determined that the majority of provinces had severe or extreme drought
risk levels (Table 2), thus a drought event is suspected as occurring or commencing across the country during these years.
The 2017 and 2018 drought risk assessments indicated most provinces as having mild or moderate drought risk levels (Table
355   2), thus a drought event is not suspected, and these were likely non-drought years. In the 2019 and 2020 drought risk
assessments, slightly more provinces displayed a severe or extreme level than a mild or moderate drought risk levels (Table
2), therefore a drought event is suspected as occurring or commencing in this period.

The literature investigated expressed that a drought event occurred in 2015-2016 as well as in 2019-2020 with all sources
360   describing 2015-2016 as experiencing severe to extreme drought impacts and most sources describing 2019-2020 as
experiencing moderate drought impact (Table 3), whilst 2017 and 2018 were reported as non-drought years (Kuleshov et al.,
2020).

In all but one source, 2014 was reported as a non-drought year. This is consistent with the drought risk assessment results,
365   with 2014 being the exception as it was suspected as a drought year from the risk assessment results and was only mentioned
as a drought year in one of the literature sources investigated (Burivalova et al., 2018). Refer to Figure 4 for the mapped
hazard, vulnerability, exposure, and risk results for 2014.

The 2014 anomaly was further investigated by the production of monthly drought risk maps throughout the year which were
370   used to determine how the risk assessment was performing throughout the year. Results show drought conditions
commencing or occurring in March-July and again in November-December, with the risk levels in November and December
being slightly more intense than those expressed in March-July (Table 4).

No statistically significant variation was displayed between the severity levels described in the risk assessment versus the
375   literature for the 2015-2016 event ($F_{18}=0.86$, $p=0.37$) and the 2019-2020 event ($F_{17}=0.71$, $p=0.25$). There was no significant

difference between the severity levels recorded for the 22 PNG provinces given by the risk assessment compared to the literature for both the 2015-2016 drought event (t_{36}=-1.70, p=0.10) and the 2019-2020 drought event (t_{34}=1.51, p=0.14). Refer to Table 5 for the severity levels of each province during the 2015-2016 and 2019-2020 drought periods given by the literature. Refer to Figures 5, 6, 7 and 8 for the severity levels of each province during the 2015-2016 and 2019-2020 drought
380 periods given by the risk assessment.

The risk assessment reported the five most at-risk provinces during the 2015-2016 period as Central (average risk index value of 0.82), West Sepik (average risk index value of 0.81), Northern (average risk index value of 0.76), Gulf Province (average risk index value of 0.75), and West New Britain (average risk index value of 0.74) (Figures 5 and 6). Similarly,
385 during the 2019-2020 period, Central (average risk index value of 0.70), Southern Highlands (average risk index value of 0.67), Gulf Province (average risk index value of 0.66), West Sepik (average risk index value of 0.64), and Northern (average risk index value of 0.64) were the five most at-risk provinces (Figures 7 and 8).

Northern, West Sepik and West New Britain were mentioned in the literature among the most affected provinces during the
390 2015-2016 period, however Central and Gulf Province were not included among the most affected (Table 5). For the 2019-2020 period, Central, Southern Highland, Gulf Province and Northern were mentioned among the most affected provinces in the literature (Table 5). However, West Sepik was not mentioned in any of the sources investigated.

Results display a valid identification of a strong drought event in 2015-2016 and moderate drought event in 2019-2020 by
395 the risk assessment. The strong event which occurred in 2015-2016 is further detailed by monthly risk index maps indicating the transition of most provinces into extreme drought risk levels in July 2015. Table 6 shows the heightening of drought risk from November 2014 to July 2015 for most provinces, with drought risk levels peaking in October-December 2015 and then slightly reducing at the commencement of 2016.

4. Discussion

400 ### 4.1 PNG drought events indicated by risk assessment

The drought risk assessment methodology used in this study was validated through a historical risk assessment paired with a literature review. As expected, the drought risk assessment identified a suspected drought event occurring or commencing in 2015-2016 as well as in 2019-2020; literature confirmed the occurrence of these suspected drought events in PNG.

405 It is widely reported that a strong drought event commenced in PNG at the beginning of 2015 and reached its peak during 2016 (Kuleshov et al., 2020; Chua et al., 2020; Gwatirisa et al., 2017; Jacka, 2020; Varotsos et al., 2018; Rimes and Papua New Guinea National Weather Service, 2017). Kuleshov et al. (2020) attributed the drought of 2015-2016 to a strong El

Niño which occurred during these years. This strong El Niño phase was paired with a positive IOD phase; the interacting impacts of both climate drivers resulted in devastating negative rainfall anomalies across the entirety of PNG (Bhardwaj et
410 al., 2021b). It is explained in the literature that the 2015-2016 drought event affected approximately 40% of PNG's population, with drought-caused food shortages impacting half a million people throughout PNG's provinces (Kuleshov et al., 2020).

A recent drought event occurring in PNG, which commenced in 2019 and continued throughout 2020, has been recently
415 reported by various sources (Johnson et al., 2019; Bang and Crimp, 2019; Null, 2021; Papua New Guinea National Weather Service, 2020). Unlike the 2015-2016 drought event, drought conditions in PNG during 2019-2020 were due to a La Niña event. The second half of 2020 saw the emergence of a moderate to strong La Niña event that is causing extreme weather in many parts of the world. A neutral IOD phase was also evident, thus La Niña impacts were not exacerbated by the IOD. The impacts of La Niña on rainfall patterns vary across PNG. In the past, La Niña has resulted in wetter conditions over most of
420 the country, except in the eastern islands of Milne Bay region (Food and Agriculture Organisation of the United Nations, 2021). The 2019-2020 La Niña caused below-average rainfall in PNG, particularly in the Northern parts of PNG (Food Security Cluster et al., 2021). With La Niña alone influencing the 2019-2020 event, it was expected to be weaker than the strong drought of 2015-2016 (driven by both El Niño and positive IOD).

425 The risk assessment further showed that the drought risk severity levels identified for each PNG province during each identified drought event (2015-2016 and 2019-2020) differed. The 2015-2016 drought risk maps displayed severe and extreme drought risk levels throughout all PNG provinces, whereas provinces showed moderate drought risk levels during the 2019-2020 drought. Thus, the 2015-2016 event was accurately reported as more extreme, in terms of drought risk, than the 2019-2020 event, and would therefore be expected to have caused more extreme impacts on PNG communities. As
430 anticipated, the literature details extreme negative impacts of the 2015-2016 drought and moderate negative impacts of the 2019-2020 drought.

The results also provided evidence as to which specific provinces were most at risk during each drought period. Central, West Sepik, Northern and Gulf Province were indicated by the risk assessment to be among the five most at-risk provinces for both the 2015-2016 and the 2019-2020 drought periods. This suggests that these four provinces are consistently at high-
435 risk to drought compared to other PNG provinces, likely to persist in the future, and therefore should be of focus for improved management resilience in the future. However, slight discrepancies were observed when the 2015-2016 period results were compared with literature findings, which challenges the validity of this conclusion.

4.2 Comparison to Literature Findings

440   The 2015-2016 drought event is consistently described in the literature as having extreme impact on local communities in each PNG province. A poverty analysis in the lowlands of PNG conducted by Schmidt et al. (2021) stated that the severe El Niño event of 2015-2016 decimated a critical amount of PNG's local crop production which left PNG communities in a food crisis. A detailed survey found that such a climate shock had critical consequences for household welfare, contributing to a rise in households below the poverty line, particularly in rural and lowland areas (Schmidt et al., 2021). A study by Mckenna

445   and Yakam (2021) similarly sought to understand the effects of climate change felt by local people in PNG, specifically focusing on the local market sellers in Madang Province. Interview results indicated that adverse effects of the 2015-2016 drought hazard event were experienced by locals in Madang Province, particularly by farmers, who described serious negative impacts on planting and overall agricultural production (Mckenna and Yakam, 2021). In an assessment of village food needs after a disaster event in PNG by Kanua et al. (2016), the negative impacts of the 2015-2016 drought are further

450   emphasized. It is stated that even in locations that commonly experience drier conditions, where farmers adjust their agricultural processes accordingly, the dry conditions were so extreme throughout 2015-2016 that such farmers suffered crop loss (Kanua et al., 2016). Resultant food shortages, as well as the loss of clean drinking water particularly in Western Province and the highlands, caused death rates to increase (Kanua et al., 2016).

455   In comparison, the impacts of the 2019-2020 drought event are primarily discussed as moderate rather than severe or extreme. However, the effects of the 2019-2020 drought event have not been widely discussed in peer-reviewed literature as it is such a recent event, but there are some sources that have similarly investigated drought conditions in PNG and the resulting impacts during 2019-2020. These sources have described the negative affect of dry conditions on agricultural production and food security (Food and Agriculture Organisation of the United Nations, 2021; Food Security Cluster et al.,

460   2021). Areas mentioned as being of concern include the Gulf and Western Area, along with northern provinces and southern coastal provinces; this is consistent with the risk assessment results. The moderate rather than extreme drought impacts on the agriculture sector, as a result of the 2019-2020 drought event, may be due to soil moisture levels being relatively well maintained across PNG during this time (2019).

465   There were no irregularities with what was reported by the risk assessment and the literature regarding the most at-risk provinces for the 2019-2020 event, which suggests a high level of accuracy within the risk assessment results for 2019-2020. Whereas, when comparing risk levels indicated for specific provinces, slight discrepancies were detected for the 2015-2016 drought event results. Central and Gulf Province were indicated among the five most at-risk provinces by the risk assessment but were included in the most at-risk provinces described by the literature. This might have been because the majority (five

470   out of eight) of the 'ground-truth' sources used to investigate the impacts of the 2015-2016 drought event focused on only one aspect of drought (meteorological, agricultural, hydrological, or socioeconomic), and thus did not consider the holistic

impacts suffered by specific provinces like Central and Gulf Province (Chua et al., 2020; Burivalova et al., 2018; Varotsos et al., 2018; Schmidt et al., 2021; Gwatirisa et al., 2017). Comparatively, the risk assessment methodology of this study incorporated indicators for all types of drought's impacts to provide a comprehensive risk level for each province. It is not

475   likely that discrepancy negates the overall validity of the risk assessment methodology as it is only slight, with all other results proving the methodology to be accurate; further research should be conducted with a stronger 'ground-truth' comparison using first-hand local and expert perspectives (gathered through interviews) rather than what was recorded in the literature to verify.

4.3 The anomalous year of 2014

480   There was one discrepancy in the risk assessment results for 2014. The drought risk assessment indicated that it was a moderate drought year, whereas most literature describe it as a non-drought year, with only one source including it as a year in the 2015-2016 drought event (Burivalova et al., 2018). Upon further consideration, it is not illogical that 2014 was indicated as a year in which a drought was commencing or occurring by the risk assessment. The risk assessment may have indicated 2014 to be a drought year as it was leading up to the extreme drought risk levels during the 2015-2016 drought

485   event, and therefore may have reflected the strong risk which the following drought years posed. As the risk index provides information on not only the hazard conditions at the time investigated, but also the vulnerability and exposure conditions of the area investigated, it may be able to give some indication on the chance of drought occurring within the investigated area in the future.

490   The monthly risk assessment conducted for all months during 2014 indicated two periods in which drought was suspected as commencing or occurring, in March-July and November-December. In most PNG provinces, seasonal rainfall usually peaks between December-April with drier conditions commonly following in July-August (Regional Bureau for Asia & the Pacfic and Food Security Markets and Vulnerability Analysis Unit, 2015). Thus, the dry conditions indicated during March-July may have been due to normal seasonal rainfall patterns which usually cause drier conditions around July across PNG

495   provinces. The November-December period is more of an anomaly as it is not consistent with the normal seasonal patterns of PNG, which has rainfall peaking around December. However, this may be explained by the commencement of the strong El Niño event which then heightened into a widely reported drought event during 2015-2016. Reports of below-average rainfall were recorded as early as October 2014, for the 2015-2016 El Niño event (Regional Bureau for Asia & the Pacfic and Food Security Markets and Vulnerability Analysis Unit, 2015). For this study, this discrepancy does not reduce the accuracy or

500   invalidate the risk assessment methodology as there is a logical reason for its occurrence. In the future research, the results should be validated with further 'ground truth' investigation of what drought risk conditions were like in PNG throughout 2014 through surveys or interviews with local PNG people.

4.4 Increasing resilience through risk assessment and Integrated-Early Warning Systems

505 The combined results of this study demonstrate that the risk assessment methodology is valid; this novel methodology can be recommended for use in the future to increase the disaster risk resilience of PNG communities and inform the risk knowledge component of an I-EWS for drought. The adverse impacts caused by drought events seriously threaten PNG provinces, and if resilience to such disasters is not increased in the future, heightened drought events under climate change are likely to decimate local communities (Kuleshov et al., 2020). An I-EWS like the one conceptualised by Bhardwaj et al.

510 (2021a,b) would have the potential to efficiently inform community preparedness to drought events if implemented in PNG. However, such a system would not be efficient without accurate risk knowledge. Thus, an accurate risk assessment methodology, such as the one developed in this study, could be vital for the development of an I-EWS for drought in PNG, as well as critical to informing proactive and suitable disaster risk management strategies in local PNG communities.

515 The importance and usability of the novel risk assessment methodology developed in this research is further demonstrated by the monthly drought risk maps produced for the 2015-2016 drought event. The risk assessment accurately displayed high drought risk levels leading up to the peak of the drought in mid-2015 until November/December 2015 (Chua et al., 2020). Most provinces were indicated to have severe drought risk levels from November 2014 until June 2015, after which the drought heightened to an extreme point. The risk assessment may have informed the decision-makers of each PNG province

520 of the severity of drought risk which the commencing drought event posed to them. As a result, local communities in PNG provinces could have implemented proactive drought management strategies and been better prepared for the impacts of the drought event before the drought peaked, potentially saving lives (Kanua et al., 2016).

4.5 Study limitations

Although the risk assessment methodology was overall deemed accurate, this study was limited by several factors. The

525 validation used literature sources discussing each drought period as the ground truth for what occurred during that time. A more reliable ground-truth would have been the perspectives of local PNG people who personally experienced the drought conditions and ensuing impacts. Interviews could have been conducted like those executed by Mckenna and Yakam (2021) and Fragaszy et al. (2020). However, due to the COVID-19 situation in both PNG and Australia at the time of this study, interviews were not viable. Future research should consider interviewing local communities in each PNG province to

530 determine a more robust ground truth of the conditions and effects of each drought event investigated. The validation method was also constrained by the fact that there were limited numbers of scientifically robust literature sources reporting on the 2019-2020 drought event, as it was a recent event. The PNG National Weather Service was consulted to ensure that the results from the 2019-2020 literature sources were true and accurate.

535   Data was limited for the hazard indicator of VHI. Space-based VHI data is only available from 2014 onwards. Whereas the SPI data record dates to 2001. To have a complete hazard index in the historical risk assessment, the historical period investigated had to begin from 2014. 2014-2020 is a shorter period of analysis, which limits the number of drought events and non-drought periods occurring within, resulting in lower confidence in results. A longer analysis would provide greater confidence in the risk assessment methodology.

540

Data availability was also limited for the exposure and vulnerability indicators, thus, the data available closest to the time investigated was used. This meant that the vulnerability and exposure indices were the same for both 2014 and 2015 as the data was not updated throughout those two years. However, as half the indicators in both the vulnerability and exposure are more static rather than dynamic (excluding agricultural occupation, key crop replacement cost, population density and access

545   to safe drinking water), it is not expected that values would largely change on a yearly basis regardless, rather it would be more likely for values to change every two or three years (Aitkenhead et al., 2021). Therefore, the limited data availability for vulnerability and exposure indicators in 2014-2015 will not likely have a large effect on the credibility of the results.

Data availability is constrained throughout many SIDS like PNG; investment in open-sourced and cloud-based data

550   platforms would allow for collaboration between separate entities that have collected data so that all relevant data can be combined, stored, and accessed from the same place (Sun et al., 2020).

4.6 Further research

The risk assessment methodology developed in this research is novel; it combined the most efficient approaches of past risk assessment investigations to formulate a holistic, accurate and tailored risk assessment methodology to effectively improve

555   risk knowledge in Pacific SIDS. This methodology provides the foundation for further research regarding disaster risk management and the implementation of an I-EWS for drought in SIDS like PNG. Future research on the communication of risk assessment results to local communities is required to ensure that the risk assessment results are user centered. Additionally, further work is needed to integrate the risk assessment with the I-EWS being developed as part of CREWS activities.

560

At a policy level, it would be intended that the risk assessment would come in at a higher level than the I-EWS, so that local decision makers are informed of their disaster risk to know what to look out for in the warnings given by the I-EWS and how to act in response to such warnings (e.g. prioritizing resources in the most at-risk provinces, planning water restrictions in certain areas to avoid critical water shortages, formation and implementation of disease prevention and management plans in

565   the most at-risk regions, etc.). Ideally, a risk assessment platform communicating risk information to local decision-makers and a user-centered I-EWS would be developed and used as 'side-by-side' products aimed at informing proactive and suitable management of natural hazards in local communities.

5. Conclusion

570 The occurrence of natural hazards is expected to be exacerbated under anthropogenic climate change, with the impacts of hazards predicted to critically affect agricultural productivity, food security, and general economic productivity, severely reducing the financial and social health of local communities in Pacific SIDS. The novel drought risk assessment methodology demonstrated in this study was overall deemed valid, and thus can be recommended for use in future disaster risk management practices in vulnerable Pacific SIDS. A strong foundation for tailored and accurate disaster risk assessments has been developed, with future research required to further verify the accuracy of the methodology by

575 comparing the results to local and expert perspectives. The development of this tailored and accurate disaster risk assessment methodology is vital to improving risk knowledge for the development and implementation of an I-EWS and resilient disaster risk management strategies in vulnerable communities.

6. Appendices

6.1 Appendix A

580 Indicator selection for the Hazard, Vulnerability and Exposure Indices which contributed to the drought risk assessment of each drought event investigated is shown below.

Index	Indicator	Reason for Selection
Hazard	Standardised Precipitation Index (SPI) (3-month)	- Meteorological drought indicator. - Given 'green light' by World Meteorological Organisation (WMO) and recommended as starting point for drought hazard assessment. - Proven reliable as a drought hazard indicator in a previous drought detection study in PNG (Chua et al., 2020). - Used consistently in past drought risk assessments conducted in other countries with a drought-prone climate like PNG (Khan et al., 2008; Rahmat et al., 2014) - Quality data from Space-Based Monitoring Observations available through National Oceanic Atmospheric Administration (NOAA) and Japan Aerospace Exploration Agency (JAXA).
	Vegetation Health Index (VHI) (3-month)	- Meteorological drought indicator. - Given 'green light' by World Meteorological Organisation (WMO). - Proven reliable as a drought hazard indicator in a previous drought detection study in PNG (Chua et al., 2020). - Used consistently in past drought risk assessments conducted in other countries with a drought-prone climate like PNG (Bhardwaj et al., 2021a; Dalezios et al., 2014). - Quality data from Space-Based Monitoring Observations available through NOAA and JAXA.

Vulnerability	Percentage of Children Weighed at Clinics Less than 80% Weight for Age 0 to 4 years old (%)	- Indicator for Health Sector. - Use in reliable past studies investigating and assessing the effects of drought within study areas with similar socioeconomic characteristics as PNG (Hirvonen et al., 2020; Cooper et al., 2019). - Data is available for recent years from PNG National Weather Service (NWS) and United Nations Development Programme (UNDP).
	Agricultural Occupation (% of population employed in agriculture)	- Indicator for Agricultural Sector. - Use in reliable past studies investigating and assessing the effects of drought within study areas with similar socioeconomic characteristics as PNG (Nasrollahi et al., 2018; Mainali and Pricope, 2019). - Data is available for recent years from PNG National Statistical Office.
	Key crop replacement cost (USD)	- Indicator for Economy (also considers socioeconomic drought). - Use in reliable past studies investigating and assessing the effects of drought within study areas with similar socioeconomic characteristics as PNG (Mohmmed et al., 2018; Abid et al., 2016). - Data is available for recent years from PNG National Weather Service (NWS) and United Nations Development Programme (UNDP).
	Staple crop tolerance scores (maximum consecutive drought days tolerated (days) (14-30)).	- Indicator for Environment and Agricultural Sector (considers agricultural drought). - Use in reliable past studies investigating and assessing the effects of drought within study areas with similar socioeconomic characteristics as PNG (Antwi et al., 2015; Ayantunde et al., 2015). - Data is available for recent years from PNG National Weather Service (NWS) and United Nations Development Programme (UNDP).
Exposure	Land use (type)	- Indicator for Environment and Agricultural Sector. - Use in reliable past studies investigating and assessing the effects of drought within study areas with similar socio-geographic characteristics as PNG (Rahmati et al., 2020; Shahid and Behrawan, 2008). - Data is available for recent years from PNG National Weather Service (NWS) and United Nations Development Programme (UNDP).
	Elevation (type) (Highland/Lowland/ Average)	- Indicator for Environment and Agricultural Sector. - Use in reliable past studies investigating and assessing the effects of drought within study areas with similar socio-geographic characteristics as PNG (Han et al., 2015; Sun et al., 2020). - Data is available from open-sourced GIS platforms.
	Population density	- Indicator for Social Sector as it is an indirect indicator for infrastructure and health service accessibility. - Use in reliable past studies investigating and assessing the effects of drought within study areas with similar socio-geographic characteristics as PNG (Nasrollahi et al., 2018; Pei et al., 2018). - Data is available for recent years from PNG National Statistical Office.
	Access to safe drinking water (% of population with access to safe drinking water)	- Indicator for Social Sector and Households (also considers hydrological drought). - Use in reliable past studies investigating and assessing the effects of drought within study areas with similar socio-geographic characteristics as PNG (Limones et al., 2020; Frischen et al., 2020b). - Data is available for recent years from PNG National Statistical Office.

6.2 Appendix B

List of Indicator Data Sources:

585   1. **Hazard indicators**: SPI and VHI from NOAA database (National Oceanic Atmospheric Administration (NOAA), 2020) and JAXA database (Japan Aerospace Exploration Agency (JAXA), 2020).

2. **Vulnerability indicators**: Percentage of Children Weighed at Clinics Less than 80% Weight for Age 0 to 4 years old, Key crop replacement cost and Staple crop tolerance scores -from PNG National Weather Service (NWS) (PNG National Weather Service (NWS), 2017) and United Nations Development Programme (UNDP) (United

590   Nations Development Programme (UNDP), 2017); Agricultural Occupation -from PNG National Statistical Office (PNG National Statistical Office, 2018).

3. **Exposure indicators**: Land use -from PNG National Weather Service (NWS) (PNG National Weather Service (NWS), 2017) and United Nations Development Programme (UNDP) (United Nations Development Programme (UNDP), 2017); Elevation -Open-sourced GIS platforms; Population density and Access to safe drinking water -

595   (PNG National Statistical Office, 2018).

6.3 Appendix C

An expert weighting scheme for the relative hazard, vulnerability and exposure indicators was developed, based on the relative importance and contribution of each factor for the specific index which it informs. This weighting scheme was developed on a 0-1 scale, with 0 indicating no probable contribution to the relative index and 1 being total probable

600   contribution to the relative index (Frischen et al., 2020a; Dayal et al., 2018). The numerical weightings assigned to each indicator were determined by investigating expert weights provided in earlier studies as well as seeking advice from PNG NWS. The weights assigned to each Hazard, Vulnerability and Exposure indicator are shown below.

Index	Indicator	Assigned Weight
Hazard	SPI	0.75
	VHI	0.25
Total	1.0	
Vulnerability	Agricultural Occupation	0.2
	Percentage of Children Weighed at Clinics Less than 80% Weight for Age 0-4 years old	0.1
	Key Crop Replacement Cost	0.3
	Staple Crop Tolerance Score	0.4
Total	1.0	

Exposure	Land Use	0.35
	Elevation	0.15
	Access to Safe Drinking Water	0.3
	Population Density	0.2
Total	1.0	605

7. Declarations and Ethics Statements

This research required no ethic approvals as no human ethics research or animal ethics research was conducted. The data used in this research was open-sourced data gathered from public databases. Spaced-based observation data underwent transformation from what is publicly available. This data may be available upon reasonable request.

610 **8. Competing Interests**

The authors declare no conflict of interest.

9. Author contribution

I.A. was lead for conceptualisation, methodology, software, validation, formal analysis, writing- original draft preparation and review and editing, and visualisation. Y.K. contributed to conceptualisation, methodology, writing- review and editing, 615 research supervision, and funding acquisition. J.B. and Z-W.C. aided in formal analysis and writing- review and editing. C.S. and S.C. contributed to writing- review and editing and supervision. All authors have read and agreed to the published version of the manuscript.

10. Acknowledgements

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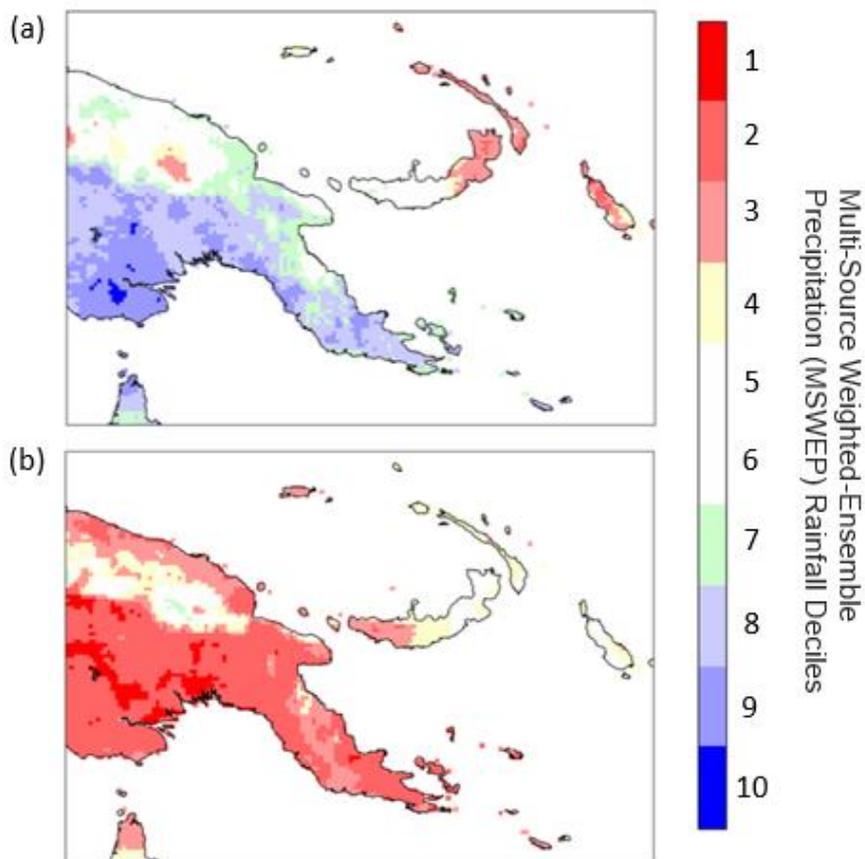
Figure 1: Multi-Source Weighted-Ensemble Precipitation (MSWEP) rainfall deciles in (a) La Niña events (La Niña years being 1988, 1989, 1995, 1998, 1999, 2000, 2007, 2010, 2011 and 2020) and (b) El Niño events (El Niño years being 1982, 1987, 1991, 1992, 1994, 1997, 2002, 2006, and 2015) compared to a base period of 1980–2020. Figure adapted from Bhardwaj et al. 2021b.

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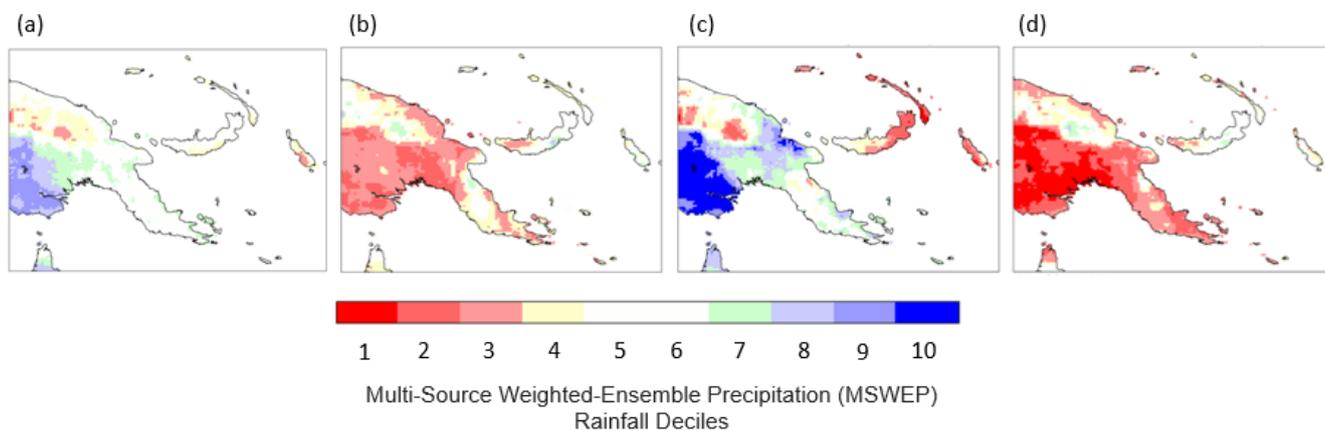
Figure 2. Multi-Source Weighted-Ensemble Precipitation (MSWEP) rainfall deciles in response to various climate drivers: (a) Negative IOD phase (during 1981, 1989, 1992, 1996, 1998, 2010, 2014, and 2016 years), (b) Positive IOD phase (during 1982, 1983, 1994, 1997, 2006, 2012, 2015, and 2019 years), (c) Negative IOD phase and La Niña ENSO phase (during 1989, 1998, and 2010 years) and (d) Positive IOD phase and El Niño ENSO phase (during 1982, 1994, 1997, 2006, and 2015 years). Deciles are compared to a 1980–2020 base period. Figure adapted from Bhardwaj et al. 2021b.

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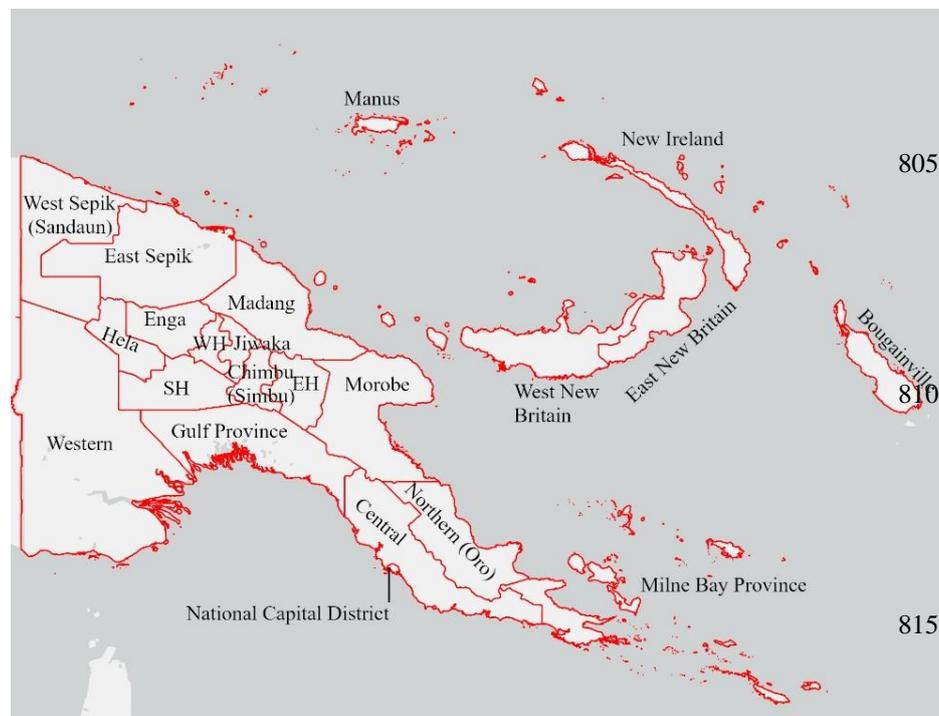
Figure 3. PNG Map indicating each of the 22 PNG provinces with shortened names for Eastern Highlands (EH), Southern Highlands (SH) and Western Highlands (WH). Map was produced using ArcGIS Pro with an open-source base map.

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Table 1. Hazard, Vulnerability and Exposure indicators selected for the PNG Drought Risk Assessment.

Index	Indicator
Hazard	Standardised Precipitation Index (SPI) (3-month)
	Vegetation Health Index (VHI) (3-month)
Vulnerability	Percentage of Children Weighed at Clinics Less than 80% Weight for Age 0 to 4 years old (%)
	Agricultural Occupation (% of population employed in agriculture)
	Key crop replacement cost (USD)

	Staple crop tolerance scores (maximum consecutive drought days tolerated (days) (14-30)).
Exposure	Land use (type)
	Elevation (type) (Highland/Lowland/Average)
	Access to safe drinking water (% of population with access to improved water sources)
	Population density (as an indicator of accessibility[6])

Table 2. Risk index levels for each PNG province calculated from the Drought Risk Assessment conducted for 2014, 2015, 2016, 2017, 2018, 2019, and 2020. Risk index levels are classified on a deepening orange colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00).

Legend:
- Extreme (0.76-1.00)
- Severe (0.51-0.75)
- Moderate (0.26-0.50)
- Mild (0.01-0.25)
- No Data

Province	Risk Index Level						
	2014	2015	2016	2017	2018	2019	2020
Bougainville	Moderate	Severe	Moderate	Moderate	Moderate	Moderate	Moderate
Central	Severe	Extreme	Extreme	Moderate	Extreme	Extreme	Severe
Chimbu (Simbu)	Severe	Severe	Severe	Moderate	Severe	Severe	Severe
East New Britain	Severe	Severe	Severe	Severe	Severe	Severe	Severe
East Sepik	Severe	Extreme	Severe	Moderate	Moderate	Severe	Severe
Eastern Highlands	Severe	Severe	Severe	Moderate	Moderate	Moderate	Severe
Enga	Moderate	Severe	Severe	Moderate	Moderate	Moderate	Severe
Gulf Province	Severe	Extreme	Severe	Moderate	Extreme	Extreme	Moderate
Hela	Moderate	Severe	Severe	Severe	Moderate	Severe	Severe
Jiwaka	Moderate	Severe	Severe	Moderate	Moderate	Severe	Severe

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[6] As there is limited data for direct indicators of accessibility in terms of road accessibility and health service accessibility, population density has been used as an indirect indicator for accessibility as it is associated with the accessibility level for each province; provinces with low population densities have more rural communities which are expected to have reduced accessibility to infrastructure (e.g. roads) and health services compared to urban communities.
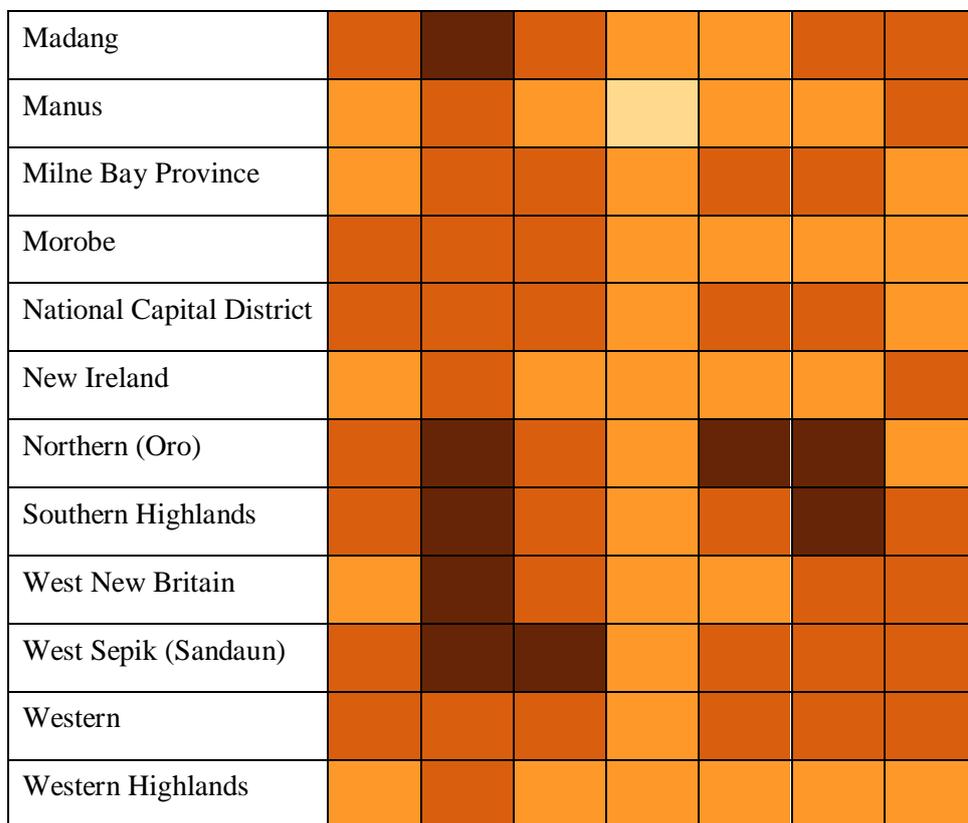
845 **Table 3. Levels of drought conditions mentioned in the literature for the time period of each of the drought events identified in the risk assessment. The number of literature sources mentioning each drought level is recorded.**

Drought Event	Mention of Mild Drought	Mention of Moderate Drought	Mention of Severe to Extreme Drought
2015-2016	0	0	8 (Chua et al., 2020; Gwatirisa et al., 2017; Burivalova et al., 2018; Jacka, 2020; Varotsos et al., 2018; Kuleshov et al., 2020; Schmidt et al., 2021; Rimes and Papua New Guinea National Weather Service, 2017)
2019-2020	2 (Johnson et al., 2019; Food and Agriculture Organisation of the United Nations, 2021)	5 (Null, 2021; Mckenna and Yakam, 2021; Food Security Cluster et al., 2021; 2019; Papua New Guinea National Weather	1 (Bang and Crimp, 2019)
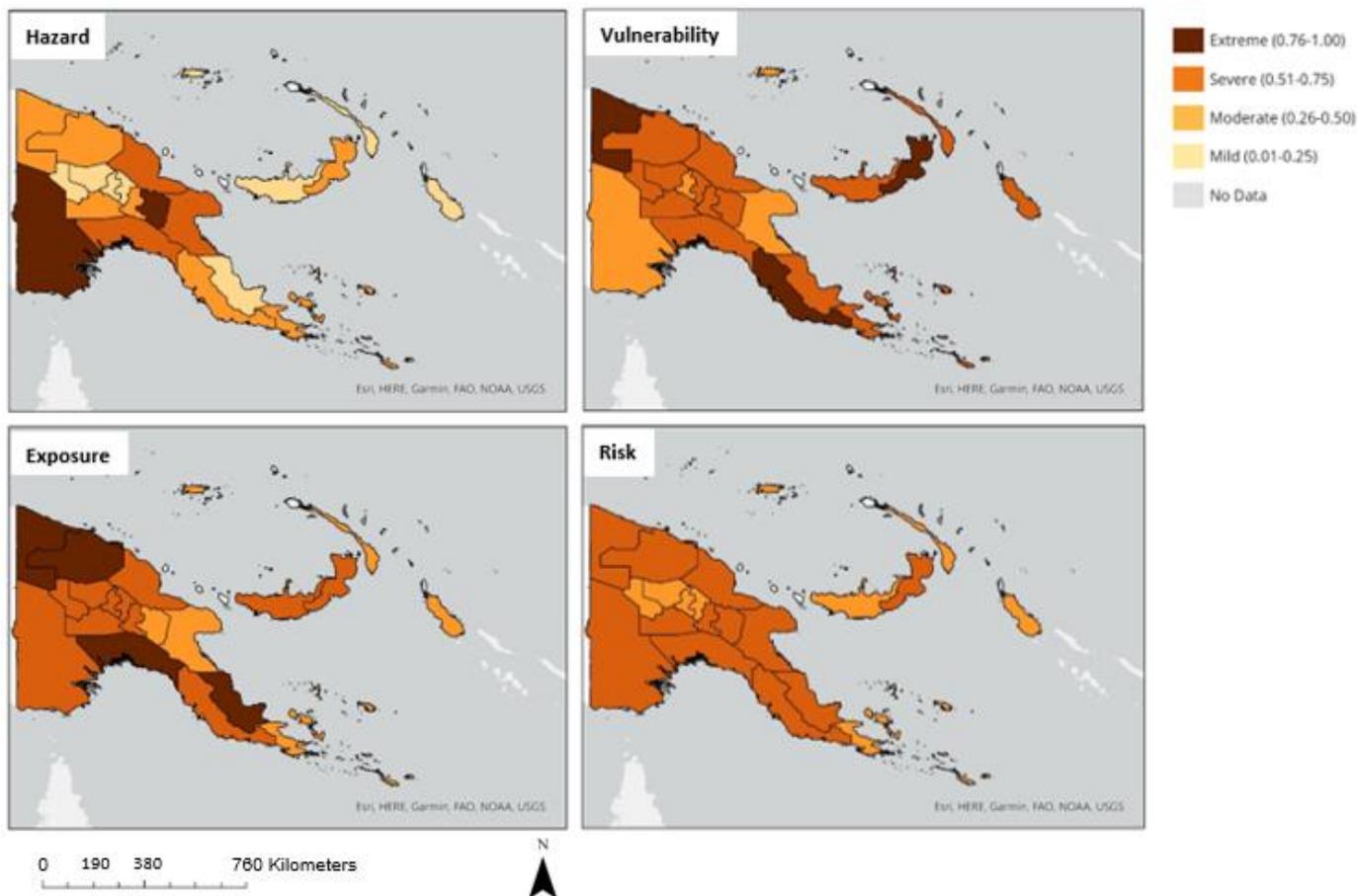
		Service, 2020)	

Figure 4. Overall drought risk maps of PNG provinces for 2014 including a drought hazard, drought vulnerability, drought
850 **exposure and drought risk map detailing the index level of each province. The index level is classified on a deepening orange**
colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00). Drought risk maps were produced
in ArcGIS Pro (Esri, HERE, Garmin, FAO, NOAA, USGS).

Table 4. Drought risk levels calculated from monthly risk assessments for each province in 2014. Drought risk levels are given for
January-December. The drought risk level is classified on a deepening orange colour scale from Mild (index values from 0.01-0.25)
855 **to Extreme (index values from 0.76-1.00).**
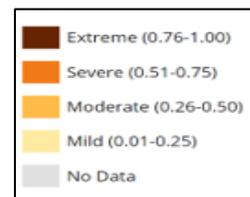
Province	Risk Index Level

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Bougainville												
Central												
Chimbu (Simbu)												
East New Britain												
East Sepik												
Eastern Highlands												
Enga												
Gulf Province												
Hela												
Jiwaka												
Madang												
Manus												
Milne Bay Province												
Morobe												
National Capital District												
New Ireland												
Northern (Oro)												
Southern Highlands												
West New Britain												
West Sepik (Sandaun)												
Western												

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860 **Table 5. Individual PNG Province mentions in literature for each drought event as well as the severity level indicated for each province in the literature.**

Drought Event	Provinces specifically mentioned	Number of sources that mentioned province	Level of impact mentioned (Mild, moderate, severe to extreme)
2015-2016	Central	5	Severe
	Chimbu	7	Severe
	Eastern Highlands	10	Severe
	East New Britain	3	Extreme
	East Sepik	1	Extreme
	Enga	6	Severe
	Gulf Province	2	Severe
	Hela	2	Severe
	Madang	2	Extreme
	Manus	2	Severe
	Milne Bay Province	2	Severe
	Morobe	6	Severe
	New Ireland	2	Extreme
	Northern (Oro)	1	Extreme
	Southern Highlands	7	Severe
	Western	4	Severe
	Western Highlands	10	Severe
	West New Britain	2	Extreme
	West Sepik	1	Extreme
2019-2020	Bougainville	1	Moderate
	Central	3	Severe
	Chimbu	1	Moderate
	Eastern Highlands	2	Moderate
	East Sepik	2	Moderate
	Gulf Province	1	Severe
	Hela	3	Severe

| Jiwaka	1	Moderate
Madang	1	Moderate
Manus	2	Moderate
Milne Bay Province	3	Severe
Morobe	1	Moderate
New Ireland	2	Mild
Northern (Oro)	1	Severe
Southern Highlands	3	Severe
Western	3	Severe
Western Highlands	3	Moderate
West New Britain	1	Moderate
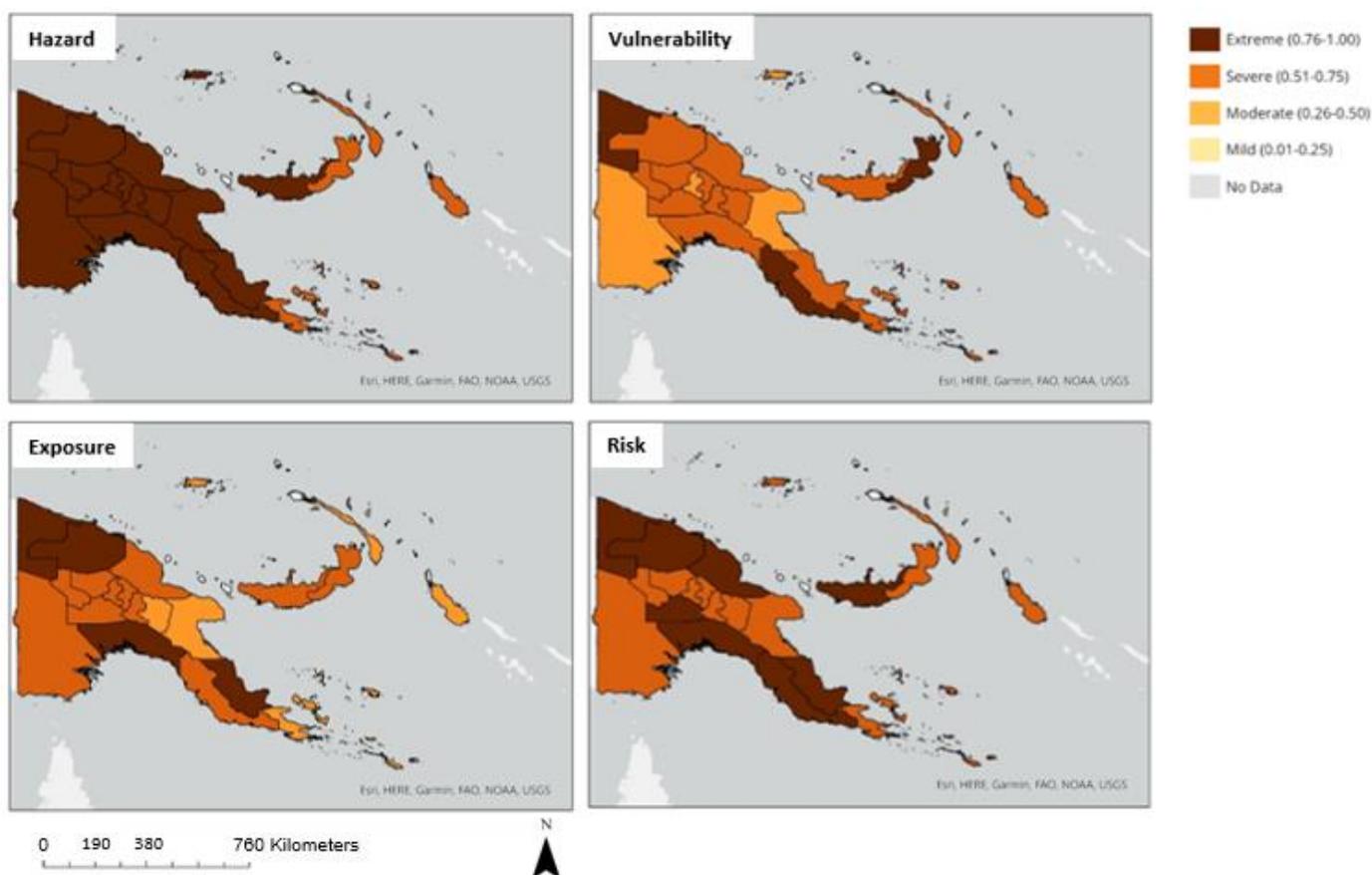
Figure 5. Overall drought risk maps of PNG provinces for 2015 including a drought hazard, drought vulnerability, drought exposure and drought risk map detailing the index level of each province. The index level is classified on a deepening orange

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colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00). Drought risk maps were produced in ArcGIS Pro (Esri, HERE, Garmin, FAO, NOAA, USGS).
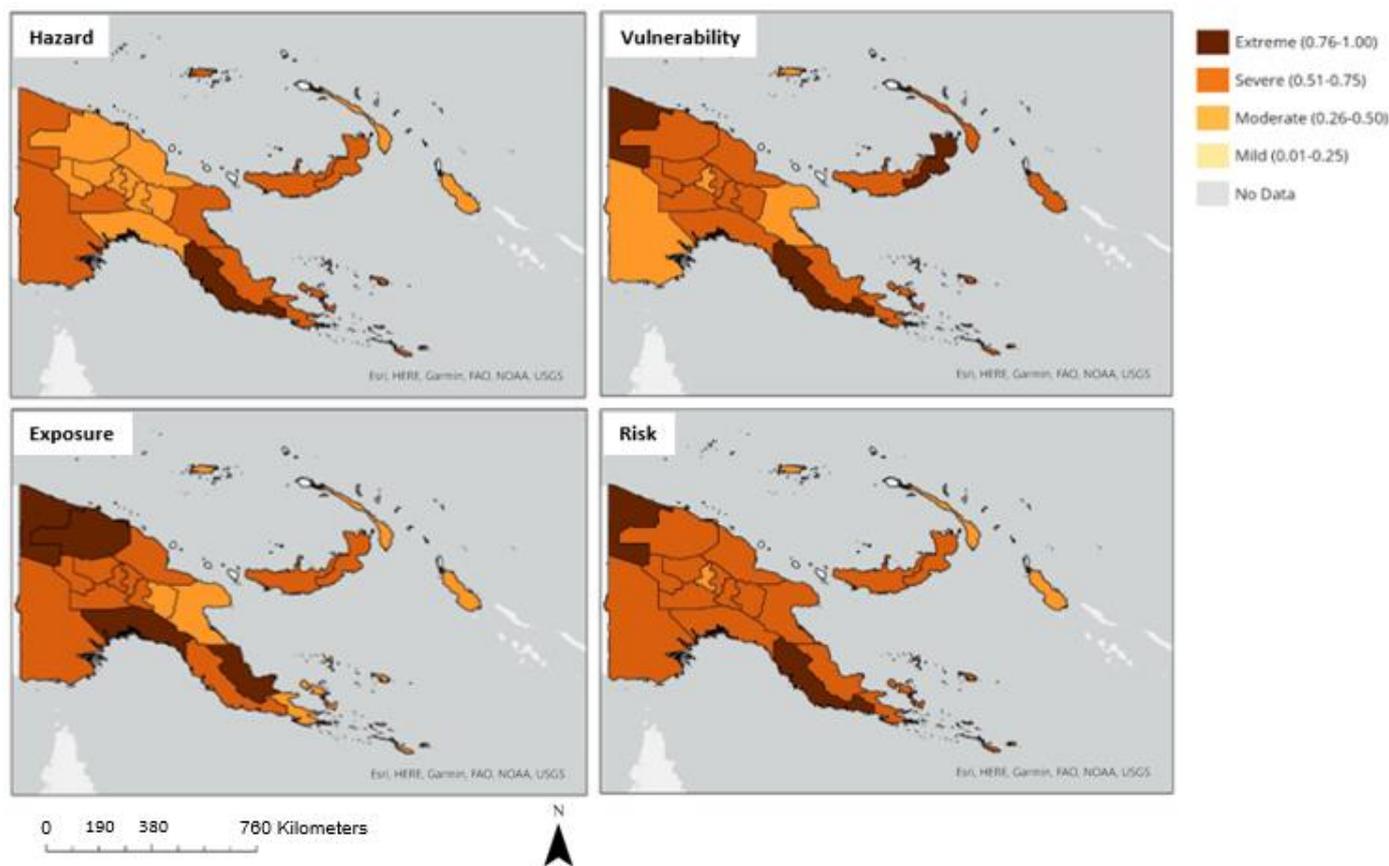
Figure 6. Overall drought risk maps of PNG provinces for 2016 including a drought hazard, drought vulnerability, drought exposure and drought risk map detailing the index level of each province. The index level is classified on a deepening orange colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00). Drought risk maps were produced in ArcGIS Pro (Esri, HERE, Garmin, FAO, NOAA, USGS).
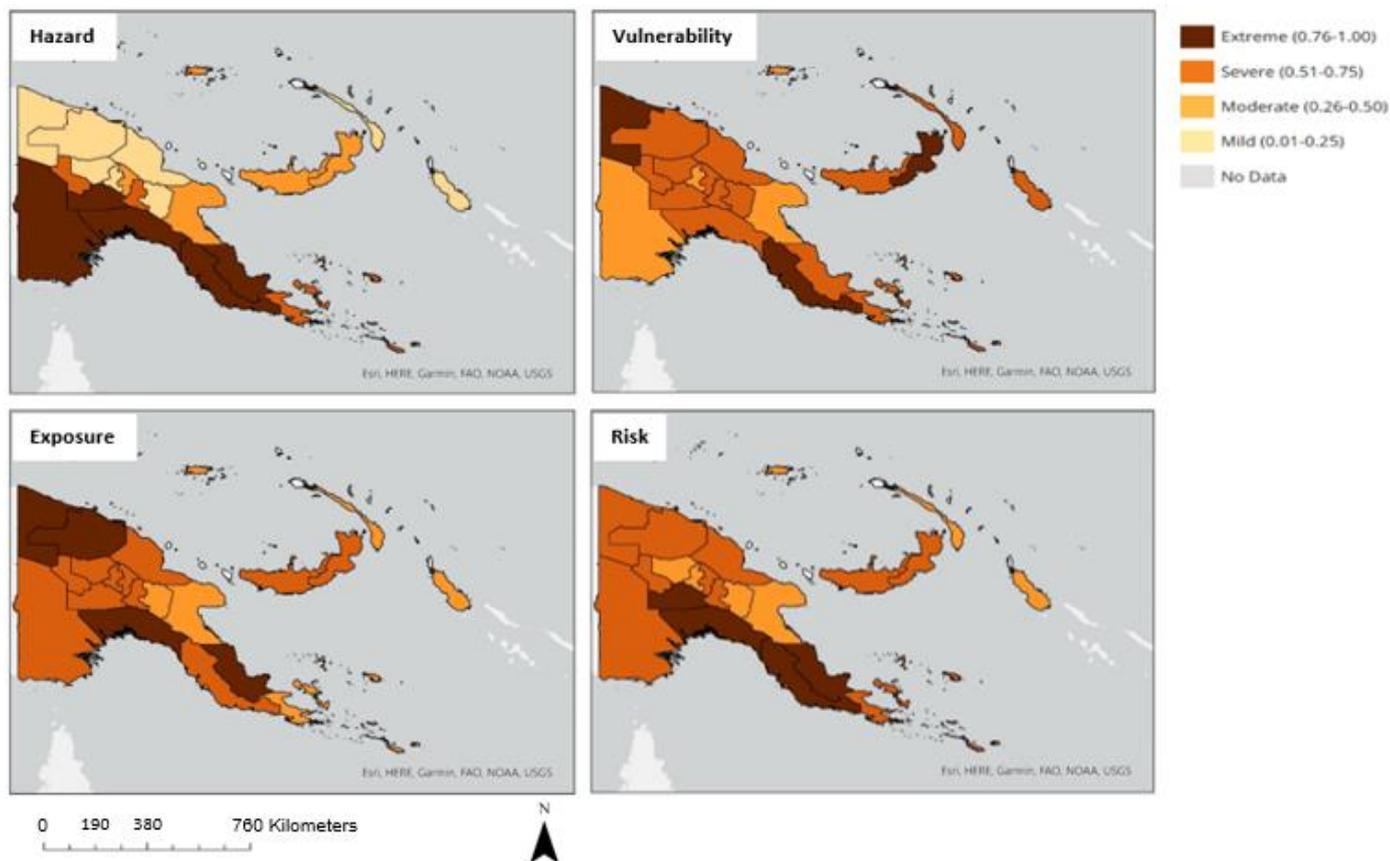
Figure 7. Overall Drought Risk Maps of PNG Provinces for 2019 including a Drought Hazard, Drought Vulnerability, Drought
875 **Exposure and Drought Risk Map detailing the index level of each province. The index level is classified on a deepening orange colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00). Drought risk maps were produced in ArcGIS Pro (Esri, HERE, Garmin, FAO, NOAA, USGS).**
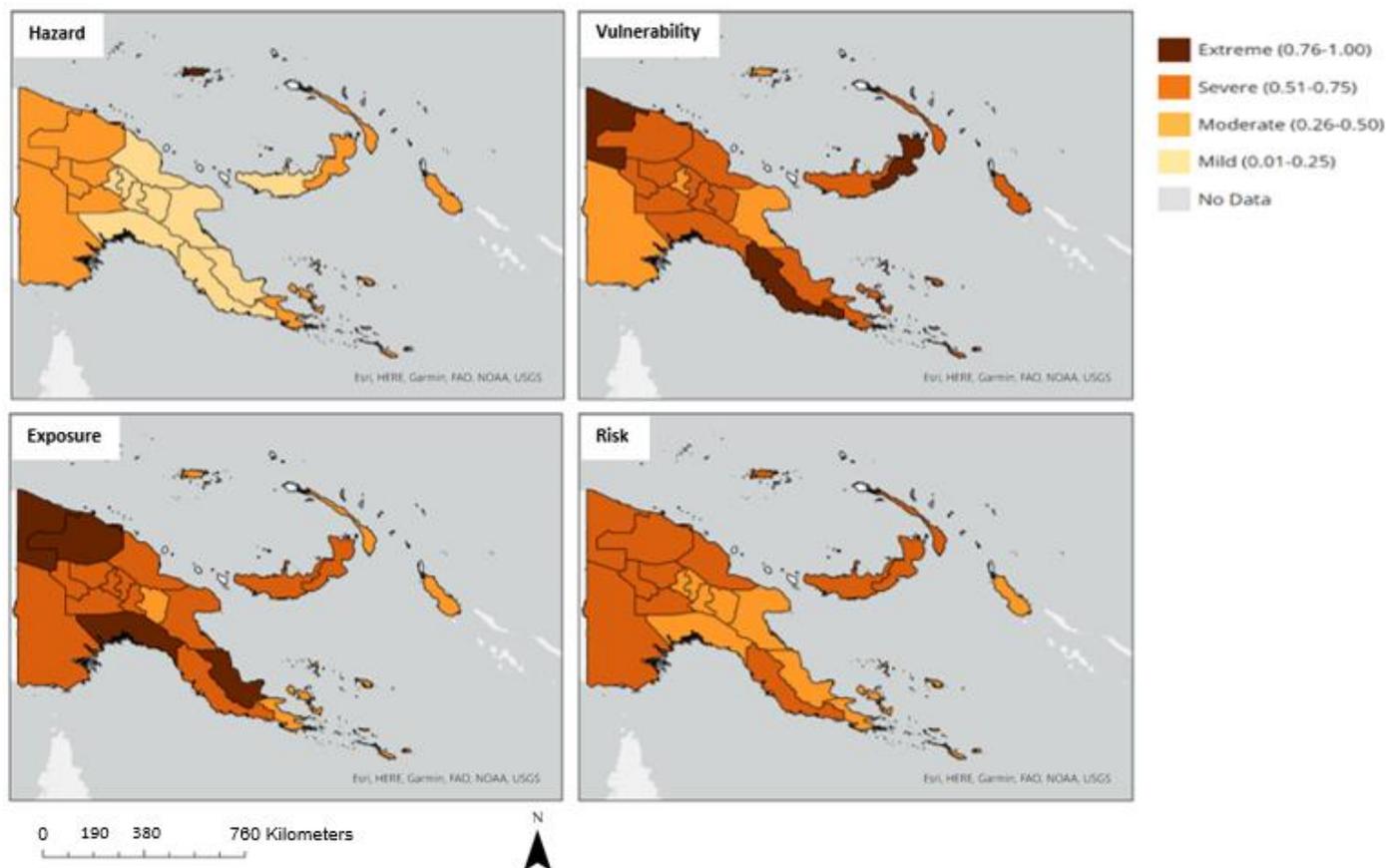
Figure 8. Overall Drought Risk Maps of PNG Provinces for 2020 including a Drought Hazard, Drought Vulnerability, Drought
880 **Exposure and Drought Risk Map detailing the index level of each province. The index level is classified on a deepening orange colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00). Drought risk maps were produced in ArcGIS Pro (Esri, HERE, Garmin, FAO, NOAA, USGS).**

Table 6. Drought risk levels calculated from monthly risk assessments for each province during the transition into the strong 2015-2016 drought conditions. Drought risk levels are given for November and December 2014, January to December 2015, and
885 **January and February 2016. The drought risk level is classified on a deepening orange colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00).**

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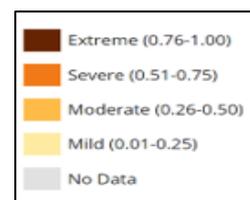
Province	Risk Index Level														
	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb

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