Validating a Tailored Disaster Risk Assessment Methodology: Drought Risk Assessment in Local Papua New Guinea Regions

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Abstract.

Climate change is increasing the frequency and intensity of natural hazards, causing disastrous 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 but are only effective 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 dynamic and tailored risk assessment methodology was developed in this research, using drought in Papua New Guinea (PNG) as a case study, by selecting rigorous and representative hazard, vulnerability, and exposure indicators, and using integrated Geographic Information Systems (GIS) processes to produce hazard, vulnerability, exposure and risk indices and maps. The validity of the risk assessment was investigated with a retrospective risk assessment of drought in PNG (from 2014-2020) paired with a literature assessment (as a ground-truth source), and a sensitivity analysis. The novel drought risk assessment methodology demonstrated in this study was overall deemed valid and robust, with supplementary improvements proposed for consideration in future investigation to further heighten accuracy. This disaster risk assessment methodology has potential for application in other Pacific SIDS for additional disaster types, to enhance the risk knowledge component of a user-centred I-EWS and guide the implementation of such a system, as well as inform improved resilient disaster risk management practices in local at-risk areas.

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). Small island developing states (SIDS) in the Pacific include some of the most hazard-vulnerable communities in the world (Bang and Crimp, 2019). 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 (Kuleshov et al., 2014). As Pacific SIDS have a highly hazard-vulnerable nature, they are of priority for future disaster risk reduction (DRR) through resilient risk management (Bang and Crimp, 2019).

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 seen as the level of appropriateness that disaster management strategies have for application at localised levels in vulnerable places. A disaster management strategy is deemed suitable if it can be independently implemented by local stakeholders and/or communities and if it addresses the specific impacts faced by local decision-makers (Aitkenhead et al., 2021). Thus, when seeking to increase disaster resilience in SIDS, the proactivity and suitability of localised disaster risk management is of critical focus (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. An effective user-centred I-EWS consists of four inter-connected components including 1. ‘Risk Knowledge’, 2. ‘Warning Service’, 3. ‘Communication and Dissemination’, and 4. ‘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 vulnerabilities that are present from which risks arise (De León et al., 2007). This 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 service component (Kuleshov et al., 2020).

As part of the Climate Risk and Early Warning Systems (CREWS) international initiative, the Bureau of Meteorology (BoM) 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 warnings and relevant drought hazard information to end-users (Kuleshov et al., 2020). While the warning service, communication and dissemination, and response capability components have already been considered (Bhardwaj et al., 2021a,b), the risk knowledge component of I-EWSs requires further investigation. Future consideration for the expansion of the risk knowledge component, specifically in vulnerable Pacific SIDS, is required to inform efficiency in I-EWSs for Pacific SIDSs, inform the resilient management of risk in local vulnerable communities, and improve the adaptive capacity of vulnerable locals (Pulwarty and Sivakumar 2014).

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 in SIDSs, is disaster risk assessment (Chen et al., 2003; Rahmati et al., 2020). Disaster risk assessments analyse the risk of natural 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 that are of priority for improved risk management.

It is widely accepted that there are two types of risk assessments: static and dynamic. Dynamic disaster risk assessments consider both the spatial and temporal aspects of disasters, using historic and periodically updated data. Additionally, dynamic assessments incorporate not only hazard monitoring indicators, but also vulnerability and exposure indicators (Mosquera-

Machado and Dilley, 2009). Most risk assessments that have been previously conducted have been static assessments (van Riet, 2009). Static assessments provide an estimate of risk factors for a discrete moment in time and space, usually considering only one or two components of risk (e.g only hazard) (Aerts et al., 2018) (Hagenlocher et al., 2020). Dynamic assessments are recommended for use over static assessments as they provide a more holistic assessment of disaster risk; disaster risk is not static, but rather dynamic in both space and time (Hagenlocher et al., 2020).

The vitality of such dynamic risk assessments is demonstrated by Rahmati et al. (2020) in a study of drought risk in a vulnerable area of south-east Queensland, Australia. As a result of their study, Rahmati et al. (2020) provided recommendations detailing areas that are likely to experience adverse drought impacts, within which drought resilience should be improved. The dynamic drought risk assessment also had implications for utilising integrated Geographic Information System (GIS)-based mapping techniques to accurately map and visualise drought risk levels in an area to better inform drought preparedness. 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 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.

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 Pacific SIDSs. Out of those that have been conducted in Pacific SIDS, they have not utilised the most efficient methodology (Hagenlocher et al., 2019; D'Haeyer et al 2017). It is evident in the literature that the most efficient risk assessment methodology includes the following elements: the risk assessment is dynamic (Hagenlocher et al., 2020), it is conducted on the most localised scale possible (Wilhelmi and Wilhite, 2002), is tailored[1] to the area of study (e.g. specific country, state/s or province/s, or local community) (Wilhelmi and Wilhite, 2002), includes integrated GIS methodology to calculate and map risk indices as recommended by Rahmati et al. (2020), Hagenlocher et al. (2019), and Chen et al. (2003), and incorporates spaced-based monitoring products (Hagenlocher et al., 2019). Therefore, there is room for future investigation of risk knowledge in SIDSs to implement a tailored, localised risk assessment with specific spaced-based monitoring hazard indicators and appropriate 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 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.". Among the few studies seeking to validate a risk assessment methodology, various validation techniques have emerged.

[1] 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.

Validation through result comparison with historical data has been used in several studies, however the preciseness of this method has been criticised (Fekete, 2019). 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. Molinari et al. (2019) provides a critique of this validation method, 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). Although participatory research is seen as a promising validation methodology (Fragaszy et al. 2020), some 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 the national scale as well as the views of experts regarding what was experienced on the ground during the investigated period.

In Pacific SIDS, data availability is scarce, 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 in SIDS.

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 a Pacific SIDS vulnerable to climate extremes and disaster events. It is predicted to be increasingly affected by impacts from tropical cyclones, floods, and drought in the future. Such hazard events are mainly a result of two key climate drivers: the El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD).

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 (Fig. 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. Each IOD phase interacts with ENSO impacts differently (Bhardwaj et al., 2021b). The impacts of interactive IOD and ENSO phases experienced in PNG are shown in Fig. 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.), an effective drought risk assessment would not only use indicators tailored for monitoring drought in PNG, but also use a variety of sectoral indicators to encompass the overall drought risk. Such an effective drought risk assessment in PNG has the potential to inform community/provincial-scale DRR (Webb, 2020).

This study will expand on previous research with an aim to address the risk knowledge component of a user-centred I-EWS. This research seeks to demonstrate the potential for tailored risk assessments to accurately inform on disaster risk levels before, during and after a disaster event and thus contribute to more resilient disaster risk management in local areas, using drought in PNG as a case study. The study intends to develop an effective, dynamic risk assessment methodology utilising GIS integrated technique and space-based weather and climate extremes observations, conduct a unique and tailored, dynamic drought risk assessment for a retrospective period in PNG, and perform a comprehensive validation of the risk assessment results using literature records as a 'ground-truth' source. The developed risk assessment methodology is purposeful for potential future application to other disaster types in additional Pacific SIDSs.

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 (Fig. 3).
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).
-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 (Fig. 3) (Bhardwaj et al., 2021a). PNG climate also varies between years, with a dominant driver being ENSO (Fig. 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 proposed here addresses the limitations identified in previous studies (Hagenlocher et al., 2019) to achieve a tailored and accurate risk assessment. As hazard, vulnerability, and exposure components are equally considered, and the spatial and temporal aspects of drought are investigated, using retrospective and periodically updated data, the risk assessment developed here is seen as a "dynamic" risk assessment intended to highlight areas in PNG most at-risk to experiencing adverse drought impacts. This research is conducted on the provincial level within a 2014-2020 study period.

The methodology for this study was four-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 retrospective[2] 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 retrospective risk assessment.
4. Implementation of a sensitivity analysis to enhance the evaluation and validity of 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). A comprehensive indicator selection process is especially important for risk assessments in Pacific SIDS as Pacific SIDS experience a diverse array of climactic conditions that are commonly managed on the local scale by sectoral stakeholders or communities, so they require tailored, specific risk assessments to indicate disaster risk.

The risk index developed here incorporates equal components of hazard, vulnerability, and exposure, with specific indicators selected to contribute to these three components. With drought hazard covering the possible occurrence of drought events in the future, exposure considering the total population, its livelihoods and assets in an area in which drought events occur, and drought vulnerability reflecting the tendency of exposed factors to suffer adverse impacts when a drought event occurs (Sharafi et al., 2020). The equal inclusion of hazard, vulnerability, and exposure components for formulating the drought risk index is an innovative approach as past studies commonly focus on hazard without inclusion of vulnerability and exposure, especially those conducted in Pacific SIDS.

[2] This methodology follows the process of historical risk assessment validation, as in Wu and Wilhite (2004), however due to the limited data range available for selected indices, it is inappropriate to call this a historical risk assessment. It is therefore deemed a retrospective risk assessment.

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. 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). 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).

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. Additionally, indicator data was only available at certain spatial resolutions. Because of this, a standard spatial resolution was chosen for the recording of data; data was recorded at the provincial level. It is also key to note that space-based monitoring products were used when gathering data for hazard index calculations to ensure accuracy. 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.

Table 1 displays the chosen hazard, vulnerability, and exposure indicators, indicator data sources, data resolution for each indicator, and the weight applied to each indicator. Two indicators: Standardised Precipitation Index (SPI) and Vegetation Health Index (VHI) were selected to be used in the hazard index. Four indicators: Percentage of children weighed at clinics less than 80% weight for age 0 to 4 years old, Agricultural occupation, Staple crop tolerance score, and Key crop replacement cost were selected for the vulnerability index. Four indicators: Land Use, Elevation, Access to safe drinking water, and Population density were chosen for the exposure index.

Each of the chosen hazard, vulnerability and exposure indicators define drought risk levels differently. Table 2 provides the thresholds for each indicator in which 'no to mild drought risk, 'moderate drought risk', and 'severe to extreme drought risk' is signalled. To further ensure that indicators were representative of varying risk levels for PNG provinces, indicator data was checked for variance using the thresholds presented in Table 2. Data from the 2020 year was used as an example year. Provincial data was compared to determine whether there was variance in signalled drought risk levels between PNG provinces. If there was minimal variance between provinces for a given indicator, then that indicator would not likely give much insight to the differing levels of risk across PNG and would not be highly appropriate for the inclusion in the calculation of drought risk indices. In the case of this study, all selected indicators displayed variance, and therefore were confirmed for inclusion in the calculation of risk indices. Once it was clear that each indicator had variance in the PNG provincial data, the raw data was uploaded to ArcGIS Pro.

2.2.2 Methodology: Part 2

Retrospective (2014-2019) and current (2020) data detailing hazard, vulnerability, and exposure conditions, in each of the 22 PNG provinces for each year within the 2014-2020 study period in PNG, was used to develop a risk index for each year to determine the yearly drought risk levels and whether it is suspected that a drought event(s) occurred. Integrated-GIS methodology for mapping risk in each study region was used to display yearly risk levels for 2014-2020. It was then determined whether a drought event was suspected as occurring across PNG in each of the years assessed. 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 and out of drought during any strong drought event indicated by the risk assessment.

To calculate the hazard index, vulnerability index, and exposure index, yearly indicator 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). *Fuzzy* logic is processed in ArcGIS Pro through the *fuzzy* function which requires the assignment of *fuzzy* membership classes to data. Prior to the performance of the *fuzzy* function, *fuzzy* membership 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*[3] and *fuzzy large*[4]. *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 the mean value in the historical records for indicator data (historical records meaning all available past data; this differs for each indicator e.g. SPI data is available from 2001 onwards). This ensured that the data was standardised on both a spatial and temporal scale.

The indicator *fuzzy* values for each year were mapped on the provincial scale as yearly raster layers in ArcGIS Pro[5]. Thus, a 2014, 2015, 2016, 2017, 2018, 2019, and 2020 raster layer was mapped on the provincial scale for each of the ten indicators. Indicator *fuzzy* values, displayed on these yearly maps, were recorded and used to calculate hazard, vulnerability, and exposure indices for the each of the 22 PNG provinces.

Prior to index calculations, numerical weights were assigned to each indicator contributing to the hazard, vulnerability and exposure indices based on an expert weighting scheme informed by past studies and advice from the PNG National Weather Service. The weights assigned reflected the relative importance and contribution of each indicator to the specific index it informs. This weighting scheme was on a 0-1 scale, with 0 indicating no probable contribution to the relative index and 1 being total probable contribution to the relative index (Frischen et al., 2020; Dayal et al., 2018). The weights assigned to each hazard, vulnerability and exposure indicator are shown in Table 1. By applying weights to indicators, the potential affect of anomalies in individual indicator data is reduced. For example, hazard data anomalies are expected as there is commonly a lag between dry signals from SPI and VHI. The effects of dry conditions recorded in SPI are commonly seen leading up to and during a drought event, whereas the vegetative affects recorded by VHI can sometimes lag and can only become evident once a drought event has commenced. Thus, SPI is likely to be more informative in signalling drought events, meaning it is appropriate to give it a greater weighting than VHI in the hazard index.

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

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

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

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.

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

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

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

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 for each province, spatial maps of the area covering the 22 provinces of 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 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 (Dayal et al., 2018; Frischen et al., 2020). This process was repeated to calculate a drought risk index for each year and month under investigation.

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. A nationwide drought event was suspected when most 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 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, impacting the national economy (Kanua et al., 2016).

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. Literature sources on this topic were analysed for the period of 2014-2020 to determine when drought events were recorded. The events recorded in the literature were compared to those identified by the risk assessment. The events identified by both the literature and risk assessment were further analysed by comparing the severity of each event indicated by the risk assessment and the severity described in the literature.

Two events were indicated in the risk assessment and confirmed in a literature investigation of openly accessible sources mentioning drought conditions in PNG from 2014-2020 (a 2015-2016 drought event and a 2019-2020 drought event). Reputable literature sources detailing drought conditions around the time of each event indicated by the risk assessment were analysed to determine the ground-truth of the drought event severity and impact.

Three severity levels were used to classify the strength of the events indicated in the assessment and literature: mild, moderate, and severe to extreme. For the risk assessment, the strength of each identified drought event was determined as mild, moderate, or severe to extreme, based on the risk level pattern observed across PNG overall (Table 3). Table 4 displays the information used to formalise the link between impacts reported by literature sources and the three severity classes. The level most clearly aligned with the details provided by each source was recorded. Additionally, any mention of specific provinces experiencing impacts was recorded.

Eight sources were assessed for each drought event, thus 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; Golden Gate Weather Services, 2021; Mckenna and Yakam, 2021; Food Security Cluster et al., 2021; Bidault et al., 2019; Papua New Guinea National Weather Service, 2020; Bang and Crimp, 2019)). The records in the literature were not extensive for the 2019-2020 drought event in PNG with only eight reputable sources identified as having mention of this event, whereas an array of records was available for the 2015-2016 drought 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 equal number of eight sources each were selected for the analysis for each event.

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) two types of statistical tests were performed: F-test and t-test[6]. Both tests were conducted for each event investigated (2015-2016 and 2019-2020). The F-test was firstly conducted to determine whether there were equal variances between the provincial risk levels displayed in the risk assessment, and the impact levels within provinces expressed in the literature, for each drought event. The F-value (test statistic), degrees of freedom and the two-tailed p-value indicating the level of marginal 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 between the drought risk levels indicated by the assessment and the impact levels indicated in literature for each province during each drought event. The t-value (test statistic), degrees of freedom and the two-tailed p-value were recorded. The use of two-tailed p values instead of one-tailed p values was due to the small number of literature sources investigated. Two-tailed p-value accounts for smaller sample sizes and tests for the possibility of positive or negative differences in the samples. Test assumptions were checked by plotting the data distribution on boxplots. All assumptions were met, thus the tests proceeded. All statistical tests used $\alpha = 0.05$.

2.2.4 Methodology: Part 4

A sensitivity analysis was conducted for the risk assessment results to determine the likely contribution of indicators to the index they inform. Sensitivity analysis is used to determine how different values of an independent variable (in this case individual indicators) affect a particular dependent variable (in this case the hazard, vulnerability of exposure index) under a provided set

[6] Statistical analyses were performed in Microsoft Excel.

of assumptions. A Sensitivity Index (SI) was calculated, indicating the sensitivity of the index in question to the individual indicator in question. A high SI means high sensitivity, vice versa, with 'sensitivity' meaning the magnitude of the index reaction to changes in indicator data.

The 2015 year was used as a case study for the sensitivity analysis, as it was the most critical drought year indicated by the risk assessment and identified in the literature. All indicator and index data for each province in the 2015 year, was inputted into excel. Data tables were created for each indicator in each index. For example, a separate data table was made for SPI and VHI which contribute to the hazard index. In the data table, the indicator data value in question was instructed to change in 0.1 increments (spanning from 0.1 to 1). Using the What-If analysis function in Microsoft Excel, these data tables were populated with output results, in this case the relevant index (hazard, vulnerability, or exposure) output in response to the change in the indicator value in question. The output values were then used to calculate the Sensitivity Index (SI). The SI was calculated based on an equation (equation 4) deemed useful in past studies (Farok and Homayouni, 2018).

$$SI = (D_{max} - D_{min})/ D_{max} \qquad (4)$$

where D_{max} is the output result (hazard, vulnerability, or exposure value) when the indicator value in question is set at its maximum value and D_{min} is the result for the minimum indicator value.

This process was repeated for all provinces, meaning an SI was produced for each of the 10 indicators used in this study, for each of the 22 provinces investigated. An overall SI for each of the 10 indicators was calculated from averaging the provincial SI values. The higher the indicator SI is, the more sensitive the relative index (hazard, vulnerability, or exposure) is to that indicator. The average SI value was used to rank each indicator in terms of sensitivity (first being the most sensitive) in each of the three indices (hazard, vulnerability, and exposure). As it is known that indices comprising of indicators with a high sensitivity index (SI) have a likely reduced robustness, a credibility rank was able to be given to each indicator in each of the three indices, based on the sensitivity results (first being the most credible for inclusion in the index) (Anand e t al., 2019).

3. Results

3.1 Selected indicators for risk assessment

The selected indicators are listed, and the comprehensive selection criteria is described in Tables 5, 7 and 9 in which details are provided on the reasoning behind hazard, vulnerability, and exposure indicator selection respectively. Tables 6, 8 and 10 list other potential hazard, vulnerability, and exposure indicators respectively and why each was omitted from this study.

For hazard, SPI and VHI were chosen for use in this study, and Rainfall Deficiency, the Soil Moisture Deficit Index, and the Standardised Water Level Index Normalized Difference Vegetation Index (NDVI) were not chosen for inclusion in this study.

For vulnerability, Percentage of Children Weighed at Clinics Less than 80% Weight for Age 0 to 4 years old, Key Crop Replacement Cost, Staple Crop Tolerance Scores, and Agricultural Occupation were selected as indicators, and Average household consumption of staple food, Average Household Income, Education, and Key crop production were not chosen for this study.

For exposure, Land Use, Elevation Type, Population Density, and Access to Safe Drinking Water were chosen as indicators for this study, and Access to Roads, Access to Land Resources, Access to Technology, Access to Social Networks, Access to Market, On-farm Diversification, and the Aridity Index were not selected for use in this study.

3.2 Risk assessment and validation results

The 2014, 2015 and 2016 drought risk assessment results determined that most provinces had severe or extreme drought risk levels (Fig. 4), 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 (Fig. 4), 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 level (Fig. 4), 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 describing 2015-2016 as experiencing severe to extreme drought impacts and most sources describing 2019-2020 as experiencing moderate drought impact (Table 11), 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, 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 Fig. 5 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 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 (Fig. 6).

No statistically significant variation was displayed between the severity levels described in the risk assessment versus the literature for the 2015-2016 event (F_{18}=0.86, p=0.37) (Appendix A) and the 2019-2020 event (F_{17}=0.71, p=0.25) (Appendix B). 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) (Appendix C) and the 2019-2020 drought event (t_{34}=1.51, p=0.14) (Appendix D). Refer to Table 12 for the severity levels of each province during the 2015-2016 and 2019-2020 drought periods given by the literature. Refer to Fig. 7, 8, 9 and 10 for the severity levels of each province during the 2015-2016 and 2019-2020 drought 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) (Fig. 7 and 8). Similarly, 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 (Fig. 9 and 10).

Northern, West Sepik and West New Britain were mentioned in the literature among the most affected provinces during the 2015-2016 period, however Central and Gulf Province were not included among the most affected (Table 12). For the 2019-2020 period, Central, Southern Highlands, Gulf Province and Northern (Oro) were mentioned among the most affected provinces in the literature (Table 12). 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 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. Figure 11 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.

3.3 Sensitivity Analysis Results

The validity of the risk assessment is further confirmed by sensitivity analysis results examining the robustness of the individual indices (hazard, vulnerability, and exposure) used in the assessment. All indicator SI's were below or just over 0.5, the highest being SPI with 0.56. SI values 0.5 or below are considered low, with SPI's 0.56 value still deemed relatively low, meaning that the hazard, vulnerability, and exposure indices are essentially robust rather than sensitive (Anand e t al., 2019).

The results of the 2015 case study sensitivity analysis show that the hazard index is more sensitive to SPI compared to VHI, meaning that changes in SPI affect the hazard index more greatly than changes in VHI. Thus, SPI is the indicator ranked as 1st in hazard sensitivity and 2nd in likely credibility (Table 13).

The vulnerability index is seen to be most sensitive to the Staple Crop Tolerance Score Indicator, thus it is ranked as 1st in vulnerability sensitivity, and is likely the least credible vulnerability index. Agricultural Occupation is ranked 2nd with a slightly lower SI value than Staple Crop Tolerance Score. Child Malnourishment and Key Crop Replacement Cost have similar SI values, with the SI given for Child Malnourishment being slightly greater than that for Key Crop Replacement cost, therefore they are ranked 3rd and 4th respectively in terms of vulnerability sensitivity (Table 13).

The exposure index sensitivity analysis results show that the exposure index is most sensitive to land use, thus land use is ranked 1st in exposure sensitivity with the greatest SI value, and 4th in likely credibility. The SI values for the remaining three exposure indicators are similar, with elevation type giving an SI of 0.34, population density 0.32 and access to safe drinking water 0.31, resulting in a 2nd, 3rd and 4th ranking respectively for exposure sensitivity (Table 13).

Overall, the SI values of each indicator within each of the three indices did not greatly differ, the greatest being a 0.1 difference between key crop replacement cost (SI of 0.31) and staple crop tolerance score (SI of 0.41). Thus, credibility was similar for all indicators within each of the hazard, vulnerability, and exposure indices.

4. Discussion

4.1 PNG drought events indicated by risk assessment

The drought risk assessment methodology used in this study was validated through a retrospective, dynamic risk assessment paired with a literature review. 2014 was identified as an anomalous year, in which a mild drought was suspected as occurring. 2017 and 2018 were both identified as non-drought years. 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.

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). The monthly risk assessment conducted for all months during 2014 indicated two periods in which drought was suspected, 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 drought conditions indicated during March-July may have been due to normal seasonal rainfall patterns. The November-December drought period is not consistent with the normal seasonal patterns of PNG. 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 invalidate the risk assessment methodology as there is a logical reason for its occurrence. In future research, the results should be validated with further 'ground truth' investigation.

Although 2017 and 2018 were indicated as non-drought years, most provinces still displayed moderate levels of drought risk. Only one mild risk level was observed throughout the entire retrospective risk assessment, in Manus province during the 2017 year. This is not an unexpected result, as PNG is a highly vulnerable and exposed country to drought. Therefore, the vulnerability and exposure indices are likely to be consistently high for most years across PNG provinces. With two out of the three indices likely being at high levels, it is not radical to suggest that the final drought risk index would be higher than mild for most years. In non-drought years such as 2017 and 2018, where hazard is low but vulnerability and/or exposure is high across PNG provinces, it is the time to be proactive and improve adaptive capacity. If management practices are put in place during non-drought years to reduce the levels of vulnerability and exposure, when a drought hazard event commences the risk of destructive impacts can be reduced. If preparedness measures were put into place during 2017 and 2018, the impacts experienced during the 2019-2020 drought event could have potentially been lessened.

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 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 reported by various sources (Johnson et al., 2019; Bang and Crimp, 2019; Golden Gate Weather Services, 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 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).

The importance and usability of the risk assessment results 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. Thus, the risk assessment may have informed the decision-makers of each PNG province 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).

4.2 Comparison to Literature Findings

The risk assessment not only indicated when a drought event was likely occurring, but it also showed the differing severity levels experienced by each PNG province during each indicated drought event (2015-2016 and 2019-2020). The 2015-2016 drought risk maps displayed a severe to extreme drought event likely occurring, whereas a moderate drought event was shown as likely occurring in 2019-2020. When compared to literature findings, these results are corroborated.

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). 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 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).

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., 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 severe or 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).

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 not included in the most at-risk provinces described by the literature. This might have been because the majority (five 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 likely that this 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.

Overall, the literature findings corroborate the drought risk assessment results. Thus, it is likely that the disaster risk assessment methodology developed and tested in this research is valid. Validity can be further confirmed in additional investigations.

4.3 Sensitivity analysis

The calibre and reliability of the risk indices (hazard, vulnerability, and exposure) depend on the theoretical framework, indicator data availability, and how each index is accumulated. To enhance insight into the validity of selected indicators, and risk assessment results, a sensitivity analysis was performed. Sensitivity analysis is essential for reducing the uncertainties of the indices in the risk assessment and is therefore key to validating the risk assessment and strengthening confidence in insights users gain from the risk assessment results (Gorris and Yoe, 2014). The sensitivity analysis examines how the selected indicators affect the indices which they inform. If the dependant variable (index) noticeably changes when the input variable (indicator) changes over a range, then the dependant variable is sensitive to the independent variable. If the dependant variable does not change a lot when the independent variable varies, the dependant variable is deemed as insensitive or robust. If the indices remain robust when changing the values of the indicators that inform them, the credibility of the overall risk assessment is strengthened (Anand e t al., 2019).

As no single indicator displayed a seriously high SI value, each indicator selected for use in the risk assessment is likely credible, meaning that each of the hazard, exposure and vulnerability indices is robust and able of representing the complex processes that lead to drought risk (Anand e t al., 2019). This improves the confidence able to be had in the results presented in this paper (Anand e t al., 2019). However, a review of the weighting applied to each indicator may be appropriate, based on the different SI values expressed and differences in likely credibility for inclusion in index calculations.

The expert weighting scheme applied to the hazard indicators gave SPI a weighting of 0.75, and VHI 0.25. The sensitivity analysis ranked SPI as 1st, with an SI value greater than VHI, meaning that the hazard component is more sensitive to changes in SPI rather than VHI. Results suggest that VHI is a more credible indicator compared to SPI, therefore more weight could be distributed to VHI than what is currently.

Sensitivity analysis results suggest that the weighting of vulnerability indicators could be slightly reviewed. The vulnerability index is evidently most sensitive to changes in the staple crop tolerance score indicator; it is likely incorrect that it is weighted highest over the other indicators. Key crop average replacement cost was identified as the most credible indicator; it is logical that it should be weighted the highest among vulnerability indicators. Currently, it is weighted the second greatest. Similarly, more weight should be applied to the percentage of children weighed at clinics less than 80% weight for age 0 to 4 years old indicator as it was identified as the second most credible vulnerability indicator but is currently weighted the least. The weighting of agricultural occupation is likely valid as it is weighted second lowest and is seen to be the second lowest indicator in terms of credibility.

Similarly, results suggest that the weighting of exposure indicators could undergo minor reassignment. The exposure index sensitivity analysis results show land use to be the 1st ranked indicator in terms of index sensitivity with the greatest SI value and ranked last among exposure indicators in terms of credibility. Currently, land use is weighted the greatest among exposure indicators; it is suggested that the weighting assigned to land use should be reduced. Elevation type, population density and access to safe drinking water gave similarly low SI values, therefore they likely have similarly high credibility. However, the exposure index was seen to be slightly more sensitive to changes in elevation type over population density, and population density over access to safe drinking water. As the most credible exposure indicator, access to safe drinking water should be weighted the greatest; it is currently weighted as the second greatest. Population density is weighted the second least among exposure indicators but is identified as the second most credible exposure indicator. Therefore, it may be appropriate to assign more weight to population density in the future.

Whilst refinements to the weightings applied to hazard, vulnerability and exposure indicators are recommended in the future based on their likely credibility for inclusion in index calculations, these refinements would be minimal as the differences in SI values between indicators within each index were not serious. Thus, it is likely that the index calculations presented in this research are still valid.

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

This disaster risk assessment methodology has been developed with the intention of collaborating with an I-EWS. The combined results of this study, using drought in PNG as a case study, demonstrate that the risk assessment methodology is valid; thus, this novel methodology can be recommended for use in the future to inform the risk knowledge component of an I-EWS for disasters like drought and increase the disaster risk resilience of Pacific SIDS, like PNG. Real-time monitoring information would be provided through the I-EWS, and risk assessment would complement this by providing dynamic disaster risk information. 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 the most at-risk regions, etc.). Warnings that are framed in the context of risk would be provided on various timescales (mainly weekly and monthly updates), depending on user needs. Such warnings could be provided in climate bulletins, through warnings issued by National Weather Services (NWSs), and via online platforms. These products would include I-EWS information and results, like those given by Bhardwaj et al. (2021), paired with dynamic risk assessment information and results, and final recommendations for the proactive and suitable management of disasters in Pacific SIDS communities. Ideally, a risk assessment platform communicating risk information to local decision-makers and a platform disseminating user-centered I-EWS warnings would be developed and used as 'side-by-side' products.

4.5 Study limitations and Further Research

The disaster risk methodology developed and validated in this study provides the foundation for further research regarding disaster risk management and the implementation of an I-EWS for disasters like drought in SIDS like PNG; however, this study was limited by several factors.

The indicator selection process used in the drought risk assessment methodology was comprehensive but could be improved. To propose a set of indicators really tailored to local users, the potential users and academic experts should be consulted, as recommended by Benzie et al., (2016). In this study it was not feasible to formally gauge the perspectives of users, but advice on relevant indicators was sought by PNG NWS. In future investigation, surveys and interviews will be conducted to formally gain the perspective of locals regarding what vulnerability and exposure indicators are most appropriate for use. This feedback will inform further refinements of the risk index for drought in PNG, given data is accurate and available.

The 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 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.

This research presents a preliminary validation of a tailored risk assessment methodology which is conceptually applicable to the local level. The developed risk assessment methodology was intended to be tailored to a highly localized level, however due to data restraints, the provincial level was the most localized level able to be assessed in PNG. Data is severely limited at heightened local scales, e.g. for individual villages/cities. In the future, it would be useful to further validate the applicability of such a risk assessment methodology at a more localized scale through conducting a drought risk assessment for a specific local PNG village. Currently, such an investigation is beyond the scope of the research presented in the paper.

Data was further 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 retrospective risk assessment, the retrospective 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. It is possible that the risk assessment could be performed for years prior to 2014 by using only SPI to inform the hazard index, or by replacing VHI with a different hazard indicator with data available for a longer period. However, it is deemed that for the risk assessment to be holistic and tailored, the hazard index should not rely only on one indicator. Additionally, different hazard indicators that could potentially replace VHI, like the Normalized difference vegetation index (NDVI) (which has raw data from the 80s onwards, and SEMDP processed data from 2013 onwards) are not as accurate as VHI; VHI has been proven to be efficient and accurate, specifically for across PNG (Chua et al., 2020).

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 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 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).

Additionally, the hazard variables used were 3-month cumulated values (3-month SPI and VHI), which potentially reduces the informative value of the hazard and risk index to give a warning of high risk early enough in advance to act proactively. Furthermore, the vulnerability and exposure indicator data do not include forecasted data at all. Although forecasted data is not available for the vulnerability and exposure indicators, as a holistic drought risk index requires these two components in addition to the hazard component. The risk assessment is not intended to predict drought events before they happen, it is used to determine the risk of a drought event occurring and the relative impact that might be faced by specific provinces during a drought. Therefore, this limitation is not likely to reduce the value of the risk assessment methodology.

4.6 Research Significance and Conclusions

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 development of a 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. The risk assessment methodology developed and validated in this research is novel; it combined the most efficient approaches of past risk assessment investigations to formulate and deem valid a holistic, accurate and tailored risk assessment methodology to effectively improve risk knowledge in Pacific SIDS. The novel, dynamic disaster risk assessment methodology demonstrated in this study was overall deemed valid and robust, through a case study of drought risk assessment in PNG, and thus can be recommended for use in future disaster risk management practices in vulnerable Pacific SIDS.

In the past, risk knowledge is consistently inadequate and a standard, integrated risk assessment methodology has not been developed (Hagenlocher et al. 2019). There is a need to develop an accurate, integrated risk assessment methodology that can be applied on a multi-hazard and multi-country scale across Pacific SIDS. This is the intention of this risk assessment methodology. This methodology establishes a replicable, standard practice for expanding risk knowledge in Pacific SIDS, negating the need to develop a new methodological process for each country and each hazard experienced, which would in turn conserve time and resources. In Pacific SIDS, both time and resources are limited for risk management decision makers, thus the development of such a risk assessment methodology would be critical (Finucane 2009).

This risk assessment methodology is not only easily replicable, but it also utilises effective methodological aspects. For risk assessments to effectively inform proactive and suitable disaster risk management in local areas and vulnerable communities, they must be tailored to the area of study (Wilhelmi and Wilhite 2002). This research presents a methodology emphasising tailored risk assessment. Out of the disaster risk assessments that have been conducted in Pacific SIDS, they have been conducted on a broader (national/regional) level rather than local area (provinces) or community level (Hagenlocher et al. 2019). This assessment is conducted at the most local level possible at this time, the provincial level. In the future, it would be beneficial to investigate risk at the town/village level, however this is beyond the scope of the current research because of travel limitations, etc.

Overall, this research establishes a strong foundation for tailored and accurate disaster risk assessments, using drought in PNG as a case study, with potential for application to other disaster types in other Pacific SIDS. However, improvements are vital for future investigations applying the disaster risk assessment methodology. To increase the robustness of the hazard, vulnerability, exposure indices and subsequent risk index, the indicator selection process should include consultation with locals and other relevant users. To further verify the accuracy of the methodology, risk assessment results should be compared to local and expert perspectives as a ground-truth source, rather than literature. Additionally, future research should also consider dissemination of risk assessment results to local communities to ensure that results are user-centered and accessible. Effective future implementation of valid risk assessments to inform risk knowledge of a user-centred I-EWS and resilient risk management in local communities is critical for improving disaster risk management and the adaptive capacity of local communities to disaster events (Pulwarty and Sivakumar 2014).

6. Appendices

6.1 Appendix A

Table displaying F-test results for the 2015-2016 drought period risk assessment versus literature results.

Statistic	df (degrees of freedom)	F statistic	P-value
Value	18	0.86	0.37

6.2 Appendix B

Table displaying F-test results for the 2019-2020 drought period risk assessment versus literature results.

Statistic	df (degrees of freedom)	F statistic	P-value
Value	17	0.71	0.25

6.3 Appendix C

Table displaying t-test results for the 2015-2016 drought period risk assessment versus literature results.

Statistic	df (degrees of freedom)	t statistic	P-value
Value	36	-1.70	0.10

6.4 Appendix D

Table displaying t-test results for the 2019-2020 drought period risk assessment versus literature results.

Statistic	df (degrees of freedom)	t statistic	P-value
Value	34	1.51	0.14

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.

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, 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

This research was supported by the Climate Risk and Early Warning Systems (CREWS) international initiative and the World Meteorological Organization (WMO) through "Weather and Climate Early Warning System for Papua New Guinea” (CREWS-PNG) project.

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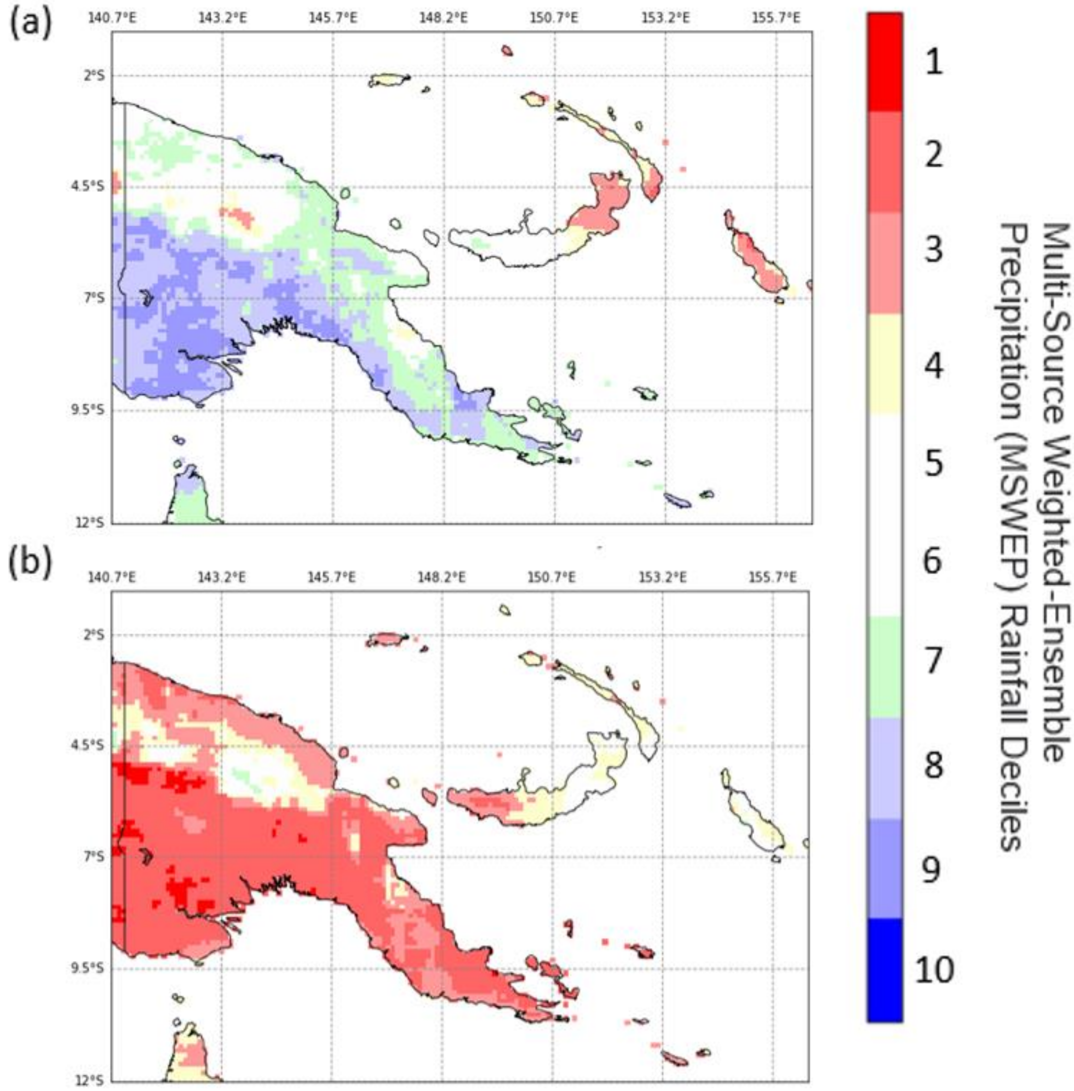


Figure 1: Multi-Source Weighted-Ensemble Precipitation (MSWEP) rainfall deciles in (a) La Niña events (La Niña years being 1988, 1989, 1995, 1998, 1999, 2000, 2007, 2010, 2011 and 2020) and (b) El Niño events (El Niño years being 1982, 1987, 1991, 1992, 1994, 1997, 2002, 2006, and 2015) compared to a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

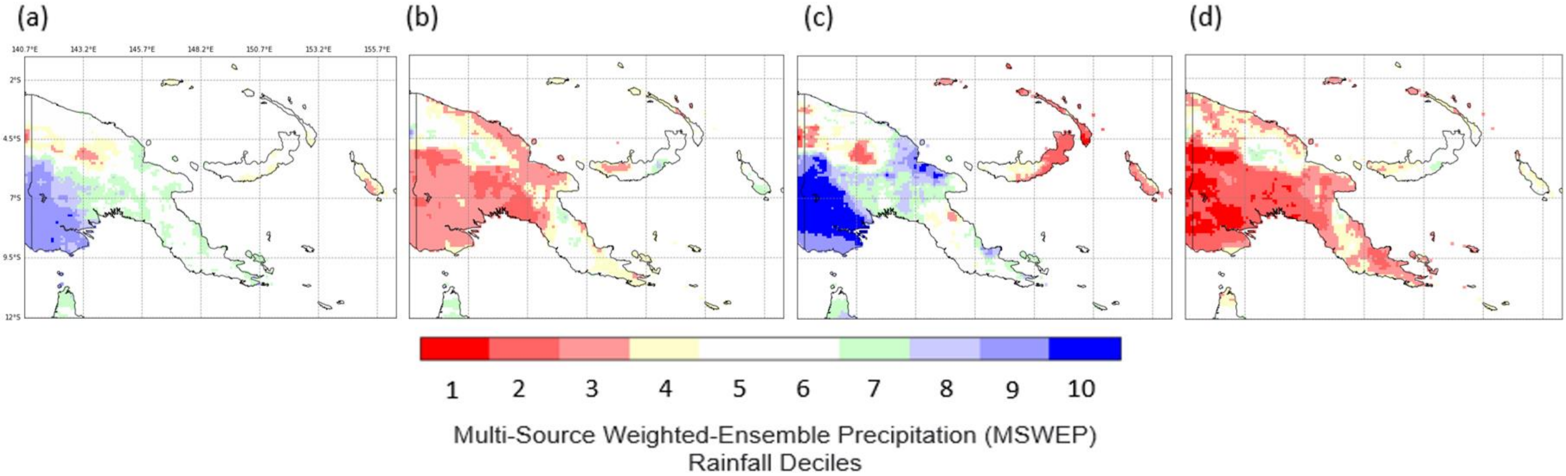


Figure 2. Multi-Source Weighted-Ensemble Precipitation (MSWEP) rainfall deciles in response to various climate drivers: (a) Negative IOD phase (during 1981, 1989, 1992, 1996, 1998, 2010, 2014, and 2016 years), (b) Positive IOD phase (during 1982, 1983, 1994, 1997, 2006, 2012, 2015, and 2019 years), (c) 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.

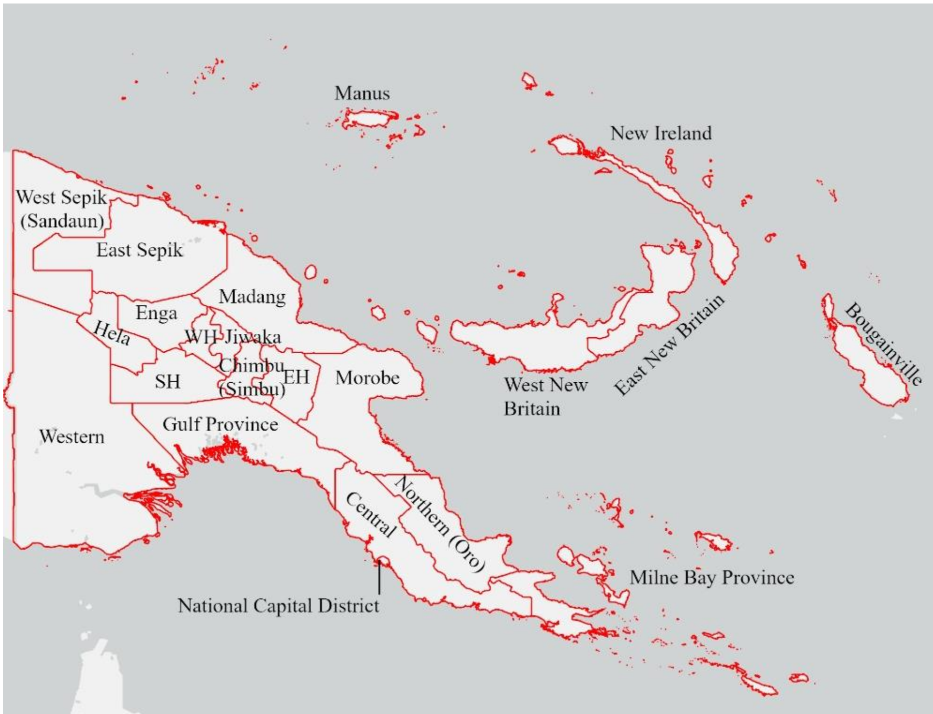


Figure 3. PNG Map indicating each of the 22 PNG provinces with shortened names for Eastern Highlands (EH), Southern Highlands (SH) and Western Highlands (WH). Map was produced using ArcGIS Pro with an open-source base map.

Table 1. Hazard, Vulnerability and Exposure indicators selected for the PNG Drought Risk Assessment. The data source, data resolution and coverage, and weighting for each indicator is included.

Index	Indicator	Data Source	Data Resolution and Coverage	Weighting
Hazard	Standardised Precipitation Index (SPI) (3-month)	NOAA database (National Oceanic Atmospheric Administration (NOAA), 2020) and JAXA database (Japan Aerospace Exploration Agency (JAXA), 2020).	Spatial- Average value for each province. Temporal- monthly and averaged yearly data available from 2001 onwards. Updated every month.	0.75
	Vegetation Health Index (VHI) (3-month)	NOAA database (National Oceanic Atmospheric Administration (NOAA), 2020) and JAXA database (Japan Aerospace Exploration Agency (JAXA), 2020).	Spatial- Average value for each province. Temporal- monthly and averaged yearly data available from 2014 onwards. Updated every month.	0.25
Vulnerability	Percentage of Children Weighed at Clinics Less than 80% Weight for Age 0 to 4 years old (%)	PNG National Weather Service (NWS) (PNG National Weather Service (NWS), 2017) and United Nations Development Programme (UNDP) (United Nations Development Programme (UNDP), 2017)	Spatial- Average value for each province. Temporal- yearly data available for study period. Periodically updated (every 1-2 years). Missing data for 2015; 2014 data was used for this period.	0.1
	Agricultural Occupation (% of population employed in agriculture)	PNG National Statistical Office (PNG National Statistical Office, 2018)	Spatial- Average value for each province. Temporal- yearly data available for study period. Periodically updated (every 1-2 years). Missing data for 2015; 2014 data was used for this period.	0.2
	Key crop replacement cost (USD)	PNG National Weather Service (NWS) (PNG National Weather Service (NWS), 2017) and United Nations Development Programme (UNDP) (United Nations Development Programme (UNDP), 2017)	Spatial- Average value for each province. Temporal- yearly data available for study period. Periodically updated (every 1-2 years). Missing data for 2015; 2014 data was used for this period.	0.3
	Staple crop tolerance scores (maximum consecutive drought days tolerated (days) (14-30)).	PNG National Weather Service (NWS) (PNG National Weather Service (NWS), 2017) and United Nations Development Programme (UNDP) (United Nations Development Programme (UNDP), 2017)	Spatial- Average value for each province. Temporal- yearly data available for study period. Periodically updated (every 1-2 years). Missing data for 2015; 2014 data was used for this period.	0.4
Exposure	Land use (type)	PNG National Weather Service (NWS) (PNG National Weather Service (NWS), 2017) and United Nations Development Programme (UNDP) (United Nations Development Programme (UNDP), 2017)	Spatial- Land use details available for each province; these details were used to score land use type exposure for each province. Temporal- static data available for study period.	0.35
	Elevation (type) (Highland/Lowland/ Average)	Open-sourced GIS platforms	Spatial- Elevation details available for each province, average type across the province was recorded. Temporal- static data available for study period.	0.15
	Access to safe drinking water (% of population with access to improved water sources)	PNG National Statistical Office (PNG National Statistical Office, 2018)	Spatial- Average value for each province. Temporal- yearly data available for study period. Periodically updated (every 1-2 years). Missing data for 2015; 2014 data was used for this period.	0.3

	Population density (as an indicator of accessibility[7])	PNG National Statistical Office (PNG National Statistical Office, 2018)	Spatial- Average value for each province. Temporal- yearly data available for study period. Periodically updated (every 1-2 years). Missing data for 2015; 2014 data was used for this period.	0.2

Table 2. Indicator thresholds that signal different stages of drought risk. These thresholds have been decided upon based on use in past studies, as well as past data trends in PNG (Rahmati et al., 2020; Nasrollahi et al., 2018; Aitkenhead et al., 2021).

Indicator	No to Mild Drought Risk	Moderate Drought Risk	Severe to Extreme Drought Risk
SPI	0.1 to 2	0 to -0.9	-1 to -2
VHI	>45	40 to 44	0 to 39
Percentage of Children Weighed at Clinics Less than 80% Weight for Age 0 to 4 years old	0 to 22	23 to 39	>40
Agricultural Occupation	0 to 24	25 to 50	>50
Key crop average replacement cost	0 to 1500	1501 to 3000	>3000
Staple crop tolerance scores	0	1	2
Land use (score)	0> to 2	>2 to 4	>4 to 6
Average Elevation (type)	1	2	3
Population density	>50	49 to 15	<15
Access to safe drinking water (%)	>60	60 to 40	<40

Table 3. The correspondence between risk level pattern observed across PNG in the risk assessment for each drought event identified, and the corresponding strength level assigned to the event.

Risk level pattern observed across PNG for indicated event	Corresponding strength assigned to the event
An approximately even number of provinces expressing moderate/severe risk level, with slightly more displaying severe.	Mild drought event.
Almost all provinces are at a severe risk level.	Moderate drought event.
Almost all provinces are at least at a severe risk level, with many expressing extreme risk levels.	Severe to extreme drought event.

Table 4. Information on the types of impacts associated with the three severity classes used to classify drought severity in the literature. Adapted from Allen & Bourke (1997).

Severity Class	Types of impacts associated
Mild	Unusually dry, but no major food supply, or drinking water or health problems OR some inconvenience with shortages in staple food but other food available, and/or must travel further to collect drinking water. Health satisfactory.
Moderate	Conditions are difficult, with food reduced and some famine food being eaten, and/or water available only at a distance, and/or some babies and elderly people unwell. No lives at risk and no related deaths reported.
Severe to Extreme	No food in gardens, famine food only being eaten, and/or water in short supply and possibly polluted, and/or increasing disease, and/or the lives of small children and elderly people at risk OR Extreme situation with only famine food available, and/or water very short, and/or many people ill, and/or small children and elderly people seriously at risk and/or related deaths reported.

[7] 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.

Table 5. Drought hazard indicators that were investigated and found to be fit for use when measuring drought hazard in PNG provinces.

Indicator	Past use description	Listed by WMO?	Reason for Selection
SPI	Used in a similar drought assessment conducted in Iran (Nasrollahi et al., 2018). It has also been used in various other past drought vulnerability assessments (Nagarajan and Ganapuram, 2015: Fallon et al., 2018). Has been evaluated and proven to be effective by (Chua et al., 2020) through a case study investigating how well SWCEM precipitation products characterised drought in PNG during the 2015/2016 El Niño event.	Yes-Green.	SPI is a space-based monitoring drought hazard indicator. It can inform on whether an El Niño or La Niña event is occurring; low precipitation is most often associated with an El Niño phase in many PNG provinces, vice versa. It has been given 'green light' by World Meteorological Organisation (WMO) and recommended as starting point for drought hazard assessment (Svoboda and Fuchs, 2016). It has also been proven reliable as a drought hazard indicator in a previous drought detection study in PNG (Chua et al., 2020) and used consistently in past drought risk assessments conducted in other countries with a drought-prone climate like PNG (Khan et al., 2008; Rahmati et al., 2014) For example, it was used in the study by Nasrollahi et al. (2018) to detect drought hazard in Iran. Iran has a hot, dry climate characterized by long, hot, dry summers and short, cool winters (Nasrollahi et al., 2018). The climate has some similarities to PNG and therefore hazard indicators are likely to be climatically suited to this study. Although the study in Iran was very broad and used nonspecific indicators that were averaged across a large range of areas being assessed, SPI has been similarly used to indicate drought hazard in additional studies and proven to be useful when assessing drought on both broad and specific scales [13, 14]. Quality data for SPI is available from Space-Based Monitoring Observations available through National Oceanic Atmospheric Administration (NOAA) and Japan Aerospace Exploration Agency (JAXA).
VHI	Used in a study of agricultural drought in Zimbabwe (Frischen et al., 2020). Has been evaluated and proven to be highly effective by (Chua et al., 2020) through a case study investigating how well SWCEM precipitation products characterised drought in PNG during the 2015/2016 El Niño event.	Yes-Green	VHI is a spaced-based monitoring drought hazard indicator that can inform on whether an El Niño or La Niña event is occurring. Chua et al. (2020) determined VHI to be highly effective in indicating the spatial and temporal aspects of the severe 2015/16 El Niño event in PNG. It has been given the 'green light' by World Meteorological Organisation (WMO) due to its ease of use and reliability (Svoboda and Fuchs, 2016). Furthermore, it has been proven useful through consistent inclusion in past drought risk assessments conducted in other countries with a drought-prone climate like PNG (Bhardwaj et al., 2021a; Dalezios et al., 2014). For example, in the Zimbabwe study conducted by Frischen et al. (2020) VHI was included as a drought hazard indicator. Although the climate of Zimbabwe is dissimilar to that of PNG, the study in Zimbabwe focused on agricultural drought risk and investigated this on specific, local community levels (Frischen et al., 2020). Therefore, the indicators used by Frischen et al. (2020) would be advantageous for use in this research, due to the importance of agriculture in PNG provinces and the subsequent focus on assessing agricultural risk in local communities with a risk assessment. However, the weighting of VHI will be reduced as it is primarily an indicator for agricultural drought risk, and although the agricultural impact of drought is of key focus in this research, a more holistic investigation is intended with additional focus on other sectors. Quality data for VHI is available through NOAA and JAXA.

Table 6. Additional drought hazard indicators investigated and found to be unfit for use when measuring drought hazard in PNG provinces.

Indicator	Past use description	Listed by WMO?	Reason for Omission
Rainfall Deficiency	Rainfall deficiency is a major factor responsible for occurrence of drought as it is the cause of subsequent soil moisture shortage for crops (Dayal et al., 2018).	No	This indicator is too broad and has questionable accuracy at the provincial level (Svoboda and Fuchs, 2016). There are more efficient indicators that similarly measure water availability that would be preferable.
Soil Moisture Deficit Index	Has been used to indicate salinity levels (Martínez-Fernández et al., 2016). This is important as salinity levels affect agricultural production (Martínez-Fernández et al., 2016).	Yes- Red	This indicator is marked with a red light by WMO because of significant obstacles that threaten the ability for use of this indicator in research. This indicator requires weekly calculations at different soil depths, which is complicated to collect and calculate (Svoboda and Fuchs, 2016).
Standardised Water Level Index	It has been used in past studies to evaluate the hazard level of drought through the identification of the amount of salt in the water, hence by its salinity concentration (Sahani et al., 2019).	Yes- Yellow	This indicator is marked as yellow due to some challenges when using this indicator for research. This indicator produces similar results to SPI, but it uses groundwater or well-level data instead of precipitation, which is more complex to collect and calculate (Svoboda and Fuchs, 2016).
Normalized Difference Vegetation Index (NDVI)	NDVI is used to identify and monitor droughts that are affecting agriculture specifically (Svoboda and Fuchs, 2016). It is a remote sensing indicator that has openly available data from spaced-based monitoring organisations like NOAA (Svoboda and Fuchs, 2016).	Yes- Green	This indicator is a popular drought hazard indicator, but it has several limitations reducing the accuracy and efficiency for use in indicating drought. Past studies have shown that anomalies are common in temporal NDVI data (Gaikwad et al. 2015). Additionally, NDVI is known to be influenced by other atmospheric and environmental factors that are not related to drought. This threatens the accuracy of NDVI for indicating drought hazard conditions as NDVI values may reflect non-drought-related stress conditions in vegetation (Jiménez-Donaire et al. 2020).

Table 7. Drought vulnerability indicators that were investigated and found to be fit for use when measuring drought vulnerability in the PNG Provinces.

Indicator	Past use description	Reason for Selection
Percentage of Children Weighed at Clinics Less than 80% Weight for Age 0 to 4 years old	Used in reliable past studies investigating and assessing the effects of drought within study areas with similar socioeconomic characteristics as PNG	This vulnerability is an indicator specific for the health sector. It has been used 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). For example, the study by Hirvonen et al. (2020) used this indicator in a case study of the 2015 drought event in Ethiopia to determine the association between drought risk and health impacts. Results of the study indicated that chronic undernutrition rates increased in drought-exposed areas that had a limited road network. The socio-economic characteristics, including those of the health sector, of Ethiopia are like PNG as they are both developing nations. Both Ethiopia and PNG have malnutrition as a main health concern, as well as lack of access to clean water and sanitation. Given the similarities between Ethiopia and PNG, and the past usefulness of this indicator

	(Hirvonen et al., 2020; Cooper et al., 2019).	in the study by Hirvonen et al. (2020), it is likely that this indicator will be an efficient drought vulnerability indicator for PNG provinces. Data is available at the provincial level in PNG for recent years from PNG National Weather Service (NWS) and United Nations Development Programme (UNDP).
Key crop replacement cost	Used 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).	This vulnerability indicator is an indicator specific for the economic sector, considering socioeconomic drought affects. It has been used 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). For example, a drought vulnerability assessment conducted by Mohmmed et al. (2018) in five agricultural-based regions of Gadaref, Eastern Sudan used key crop replacement as an indicator to examine the susceptibility of farmers. The assessment resulted in the identification of the most vulnerable regions in the study area. Sudan has similar socioeconomic characteristics to PNG, as they are both least developing countries according to the United Nations General Assembly. Like PNG, Sudan has a population vulnerable to poverty and malnourishment, with most of the population depending on agriculture for their livelihood. Due to the similarity between Sudan and PNG regarding socio-economic factors, and the usefulness of this indicator in the past study by Mohmmed et al. (2018), key crop replacement cost is likely an effective indicator of drought vulnerability in PNG provinces. Data is available on the provincial level for recent years from PNG National Weather Service (NWS) and United Nations Development Programme (UNDP).
Staple Crop Tolerance Scores	Used in reliable past studies investigating and assessing climate vulnerability and the effects of drought within study areas with similar socioeconomic characteristics as PNG (Antwi et al., 2015; Ayantunde et al., 2015).	This vulnerability indicator is specific for the environment and agricultural sector, considering agricultural drought effects. It has been used in reliable past studies investigating and assessing climate vulnerability and the effects of drought within study areas with similar socioeconomic characteristics as PNG (Antwi et al., 2015; Ayantunde et al., 2015). For example, in the study by Ayantunde et al. (2015) staple crop tolerance score was used as an indicator in a drought vulnerability assessment of three agro-pastoral communities in Niger. Niger is a least developed country with similar socio-economic characteristics to PNG, with a like reliance on the agricultural industry. As in PNG, farmers in Niger are frequently impacts by disaster events like drought, reporting detrimental impacts to crops. Due to the related socio-economic characteristics of PNG and Niger, and the usefulness of staple crop tolerance score for indicating drought vulnerability in the study by Ayantunde et al. (2015), this indicator is likely effective for assessing drought vulnerability in PNG provinces. Data is available for recent years from PNG National Weather Service (NWS) and United Nations Development Programme (UNDP). Data is available on the provincial level in PNG.
Agricultural Occupation (% of population employed in agriculture)	Used in reliable past studies investigating drought vulnerability and assessing the effects of drought within study areas with similar socioeconomic characteristics as PNG (Nasrollahi et al., 2018; Mainali and Pricope, 2019).	This vulnerability indicator is specific for the economic and agricultural sector. It has been used in reliable past studies investigating drought vulnerability and assessing the effects of drought within study areas with similar socioeconomic characteristics as PNG (Nasrollahi et al., 2018; Mainali and Pricope, 2019). For example, the study by Mainali and Pricope (2019) in Nepal used agricultural occupation as an indicator for mapping climate vulnerability of ten drought-prone villages. Results displayed that most of the study area falls in the high vulnerability category with significant spatial variation. Nepal and PNG have a similar reliance on the agricultural industry, with a significant amount of the populations employed in agriculture. The similarity between PNG and Nepal regarding the reliance on agriculture, as well as the usefulness of this indicator in the past study by Mainali and Pricope (2019) means that this indicator is most likely effective for indicating drought vulnerability in PNG provinces. Data is available for recent years from PNG National Statistical Office. Data is available on the provincial level in PNG.

Table 8. Additional drought vulnerability indicators unfit for use when measuring drought vulnerability in PNG provinces.

Indicator	Past use description	Reason for Omission
Social dependency (% population >15 and <64 years old)	Used by Frischen et al. (2020) as a drought vulnerability indicator in a drought risk assessment in Zimbabwe. Like PNG, Zimbabwe is severely affected by drought leading to adverse impacts like water shortages, declining yields, and periods of food insecurity, accompanied by economic downturns. Both countries heavily rely on the agricultural sector. The risk index gave differing risk severity levels for the different regions of Zimbabwe (Frischen et al. 2020).	Although this indicator has been used in past studies in areas with similar characteristics to PNG, it is unlikely this would be a representative indicator of drought vulnerability in PNG provinces. This is because there is unlikely to be spatial variation in indicator data, thus would not indicate the varying vulnerability levels of PNG provinces. PNG has a similarly young population across all provinces.
Average household consumption of staple food	This food consumption indicator informs on food security in households (Ibok et al. 2019). In a study conducted by Islam et al. (2022) in Bangladesh, this indicator was used to indicate climate risk of vulnerable households.	Data is severely scarce for this indicator in PNG. Therefore, it cannot readily be used as an indicator for drought vulnerability in PNG provinces.
Average Household Income	Average household income has been investigated as an indicator of drought vulnerability in previous studies, including in the research conducted by Stenekes et al. (2012). In this study, Stenekes et al. (2012) revise indicators of drought vulnerability across the Murray-Darling Basin in Australia and propose indicators to be included in future risk assessments. Average household income is proposed as a vulnerability indicator.	As a least developed country, PNG is expected to have low average household income across most provinces. The likely similarity of data for this indicator across PNG provinces reduces the value for informing on the varying vulnerability levels in PNG.
Education (Literacy rate in at least one language % of population over 10 years old)	Education level (literacy rate) has been used in past risk assessment studies as an indicator for drought vulnerability, particularly for the adaptive capacity element. In an investigation of drought risk in Nigeria, focusing on food security impacts, Ibok et al. (2019) use education level as a drought vulnerability indicator. Although Nigeria is a more developed country compared to PNG, both countries have low literacy rates compared to western countries like Australia. This has the potential to affects the ability of locals to independently implement effective drought management strategies. A study of global drought risk by Carrão et al. (2016) use education level as an indicator to derive drought vulnerability. Using the drought vulnerability, hazard and exposure indices, a drought risk index was mapped across the globe and regions of high risk were identified.	Education levels are similarly low across all PNG provinces, including the National Capital District. According to a new survey conducted in five provinces of PNG from 2006-2011, by the Asia South Pacific Association for Basic and Adult Education (ASPBAE), education level is alarmingly low across all PNG provinces (less than 5% in some cases). As there would be little variation between provinces for this indicator, it would not be valuable for informing on the varying drought vulnerability levels in PNG.
Key crop production	In an investigation of drought vulnerability in India, crop production was proposed as a useful indicator (Saha et al. 2012). Similarly, crop production was used as an indicator in a drought vulnerability assessment conducted in Indonesia, which specifically focused on food security impacts (Pangan and Pertanian, 2015).	The use in past studies investigating countries with a similar reliance on agriculture as PNG, means this indicator has the potential for use in the PNG risk assessment. However, in this research key crop production is seen more of an impact factor rather than a vulnerability factor. Staple crop tolerance or crop replacement cost a could be more specific indicators for indicating vulnerability to the effects of drought. For example,

		if a province was to have low crop tolerance scores and high replacement cost, it is likely that in a drought period the production of crops would be reduced as an impact of drought.

Table 9. Drought exposure indicators that were investigated and found to be fit for use when measuring drought exposure in PNG provinces.

Indicator	Past use description	Reason for Selection
Land Use (type)	Used 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).	This is an exposure indicator specifically considering the environment and agricultural sector. It has been used 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). For example, Land Use was used as an indicator in by Shahid and Behrawan (2008) as an exposure indicator included in the vulnerability index in a spatial risk assessment for drought in Bangladesh. In the Bangladesh study exposure was not considered as its own component of drought risk, it was included as part of the vulnerability component. Although the methodology of Shahid and Behrawan (2008) differs to the one used in this study, the consideration of land use as an exposure indicator is deemed appropriate for assessing risk in PNG. Like PNG, Bangladesh heavily relies on agriculture, with a large portion of land use dedicated to agricultural activities which have been affected by drought in the past. Data is available for recent years from PNG National Weather Service (NWS) and United Nations Development Programme (UNDP).
Elevation (type) (Highland/Lowland/Average)	Used 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).	Elevation is an exposure indicator specifically considering the environment and Agricultural Sector. Elevation affects the severity of drought in PNG, with highland areas known to be most exposed to the effects of drought in PNG in the form of frost. In the 2015/2016 drought event in PNG, high altitude areas experienced severely detrimental impacts on crops (Iese et al. 2021). Elevation has been used 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	Used 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).	Population Density is an exposure indicator for social sector, as it is an indirect indicator for infrastructure, health service, and water accessibility. It has been used in reliable past studies investigating and assessing the effects of drought (Nasrollahi et al., 2018; Pei et al., 2018). More direct indicators of accessibility like access to roads or access to markets would be better for use here, however, data availability for such indicators is extremely limited. Thus, population density is seen as the best possible indicator for accessibility to contribute to the exposure index in this research. Data is available for population density in recent years from PNG National Statistical Office.
Access to safe drinking water (% of population with access to safe	Used 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., 2020).	Access to safe drinking water is an indicator of drought exposure, particularly considering hydrological drought and its impacts on the social sector. If communities have limited access to safe drinking water, they will be more exposed to detrimental drought effects as they may have to travel further to additional water sources in times of drought, etc (Limones et al., 2020). It has been used 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., 2020). For example, when investigating an approach for identifying high drought risk areas in data-scarce regions of southern Angola, Limones et al. (2020) use access to safe drinking water as an indicator of drought exposure. Angola is expected to have similarly restricted access to safe drinking water in some areas,

drinking water)	just as with regions in PNG, as it is a Least Developed Country with locals having limited access to core resources. In the study by Limones et al. (2020) this indicator was able to help in the identification of high-risk areas to drought in Angola. The similarity between Angola and PNG mean it is likely that this indicator is suitable for use in informing a drought exposure index in PNG as well. Data is available for this indicator for recent years from PNG National Statistical Office.

Table 10. Additional drought exposure indicator unsuitable for use when measuring drought exposure in PNG provinces.

Indicator	Past use description	Reason for Omission
Access to roads	This indicator has been used in several past studies conducting risk assessments (Luh et al. 2015; Nakamura et al. 2019). For example, Nakamura et al. (2019) used this as an indicator for exposure in a drought risk assessment in Ethiopia. Results suggested that remote communities with roads connecting them to markets and other services had less exposure to drought impacts.	This indicator would be useful for indicating drought exposure; however, data is not available/accessible on the provincial level for PNG. Thus, this indicator cannot be included in the risk assessment at this time for PNG. In the future if data becomes available, then this indicator should be considered for the drought exposure index.
Access to land resources	This indicator was used in a study by Ghimire et al. (2010) which describes access to land resources as total landholding in a given area. It is explained that the higher the landholding, the lower the exposure to drought impacts. This is because landholding can serve as a cushion to absorb financial shocks by utilising it as collateral for loans or sale when needed.	This indicator is not appropriate for use in PNG, due to the nature of customary clan ownership, which over 95% of land in PNG remains under (Chand 2017). Customary clan ownership is defined as the long-established practices of PNG people. Clans rather than individual people hold most of the land in PNG provinces. Additionally, data for clan land holdings is scarce as the principles of land tenure that arise from custom are not commonly written down (Chand 2017).
Access to technology	Ghimire et al. (2010) use this indicator in an assessment of drought risk, explaining that this indicator is evidence for the adoption of improved varieties of crops or horticultural plants. Thus, access to technology likely reduces exposure.	This indicator is likely not representative of varied drought exposure among PNG provinces as it would be expected that access to technology would be relatively low across PNG. Additionally, data for this indicator is limited on the provincial level in PNG.
Access to social networks	Ghimire et al. (2010) use this indicator in an assessment of drought risk, defining this indicator as membership in social, political, or economic organisation. It is seen that access to social networks decreases drought exposure (Ghimire et al. 2010).	Data is restricted for this indicator on the provincial level in PNG. If data was restricted, it is believed that this would not be as ideal as an exposure indicator in PNG as if more relevant indicators were available like access to markets.
Access to market	Previous drought risk investigations have used access to market as an exposure indicator (Ghimire et al. 2010; Mdungela et al. 2017). It is defined as the walking distance to reach the nearest public transportation service or walking distance to the market itself. The lesser the distance, the more access to a market, which in turn means lower exposure. Walking distance is preferred over distance in kilometres, because of difference in topography in different areas of investigation.	Data is restricted for this indicator on the provincial level in PNG. It would be useful to incorporate this indicator in the risk assessment in the future if data becomes available.

On-farm diversification	Mdungela et al. (2017) used this as an indicator of drought exposure in an investigation of drought risk. On-farm diversification includes the mixing of crops and the inclusion of drought-resistance crops on farms. Mdungela et al. (2017) explain that the more diverse a farm is, the less exposed it is to drought conditions.	Data is restricted for this indicator on the provincial level in PNG. Currently, it is expected that information regarding farming types is included in the land use indicator. However, this indicator would be more specific for use if data was available.
Aridity Index	The Aridity Index has been used in past drought risk assessment studies like Lindoso et al. (2014). It is a real-time indicator in which water balance is considered with the comparison of the actual aridity to the normal aridity for a given period (Svoboda and Fuchs, 2016).	Not applicable to long-term or multi-seasonal events (Svoboda and Fuchs, 2016). Thus, it would not be appropriate to measure long-term drought; long term drought affects PNG frequently.

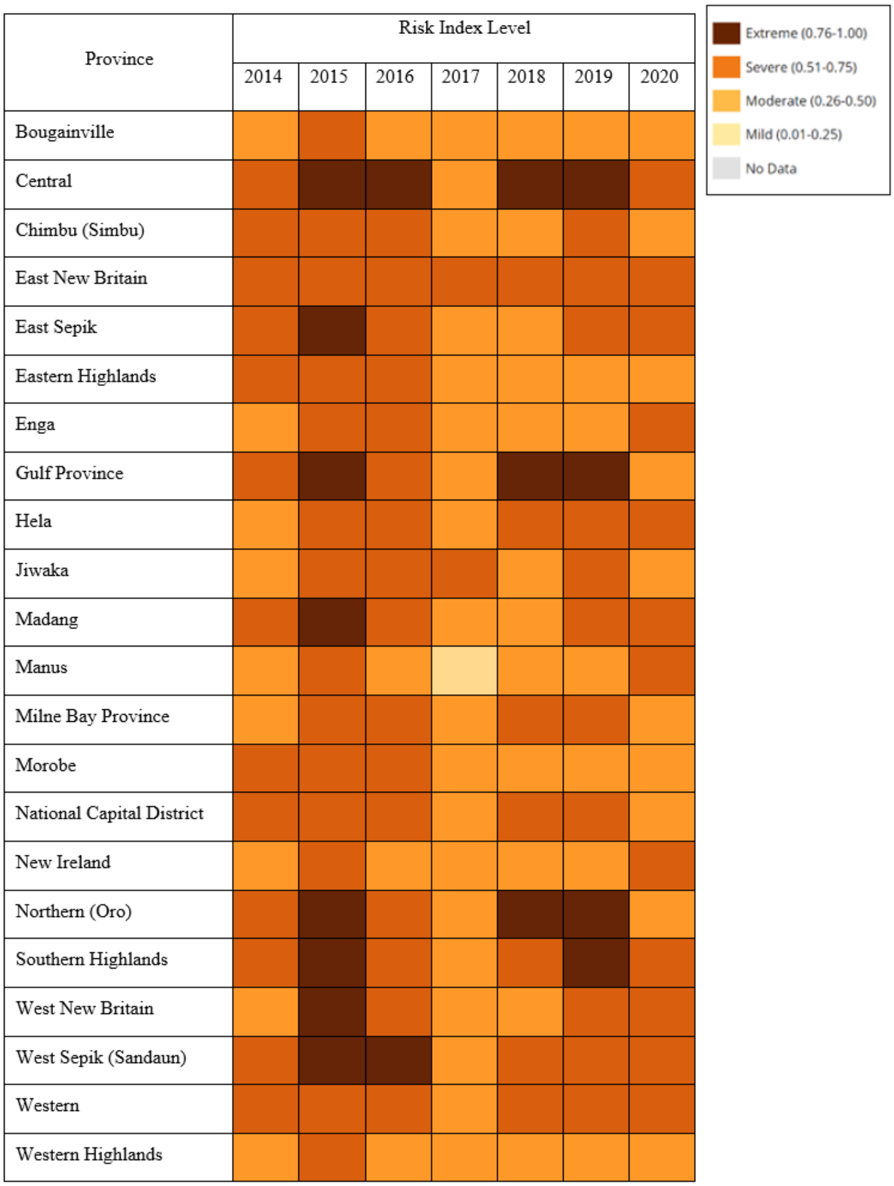


Figure 4. Risk index levels for each PNG province calculated from the Drought Risk Assessment conducted for 2014, 2015, 2016, 2017, 2018, 2019, and 2020. Risk index levels are classified on a deepening orange colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00).

Table 11. 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 (Golden Gate Weather Services, 2021; Mckenna and Yakam, 2021; Food Security Cluster et al., 2021; Bidault et al., 2019; Papua New Guinea National Weather Service, 2020)	1 (Bang and Crimp, 2019)

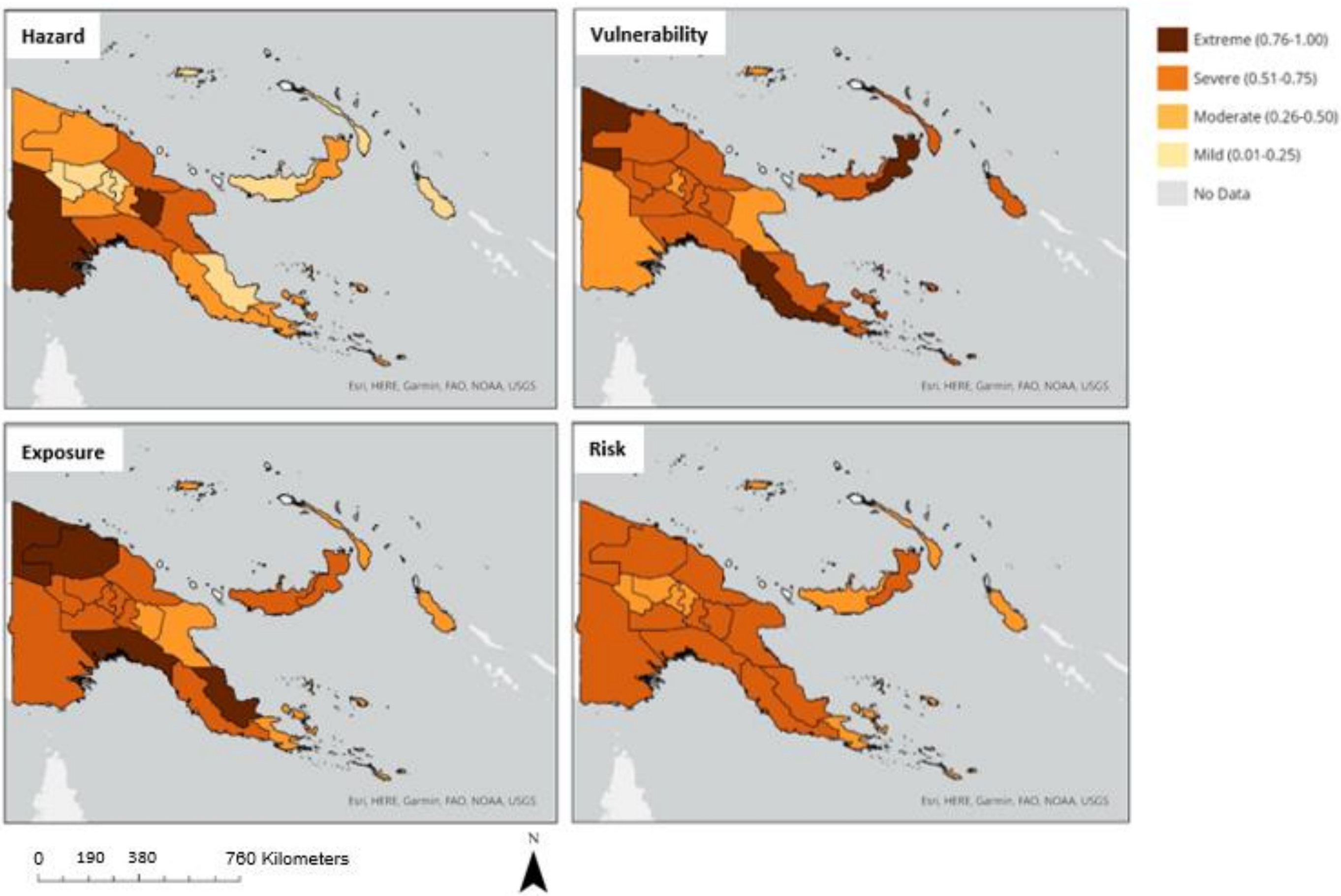


Figure 5. Overall drought risk maps of PNG provinces for 2014 including a drought hazard, drought vulnerability, drought exposure and drought risk map detailing the index level of each province. The index level is classified on a deepening orange colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00).

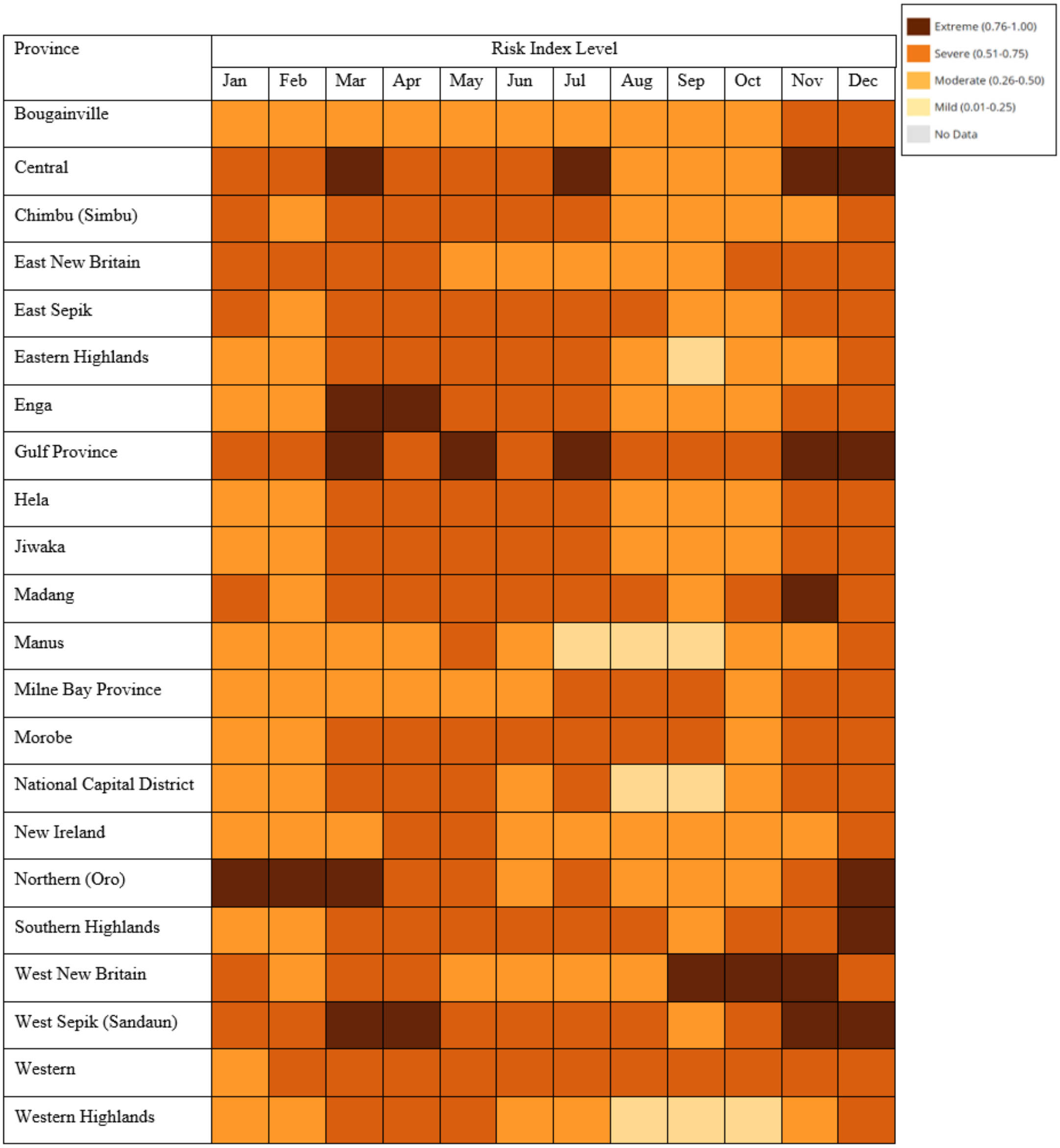


Figure 6. Drought risk levels calculated from monthly risk assessments for each province in 2014. Drought risk levels are given for January-December. The drought risk level is classified on a deepening orange colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00).

Table 12. 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

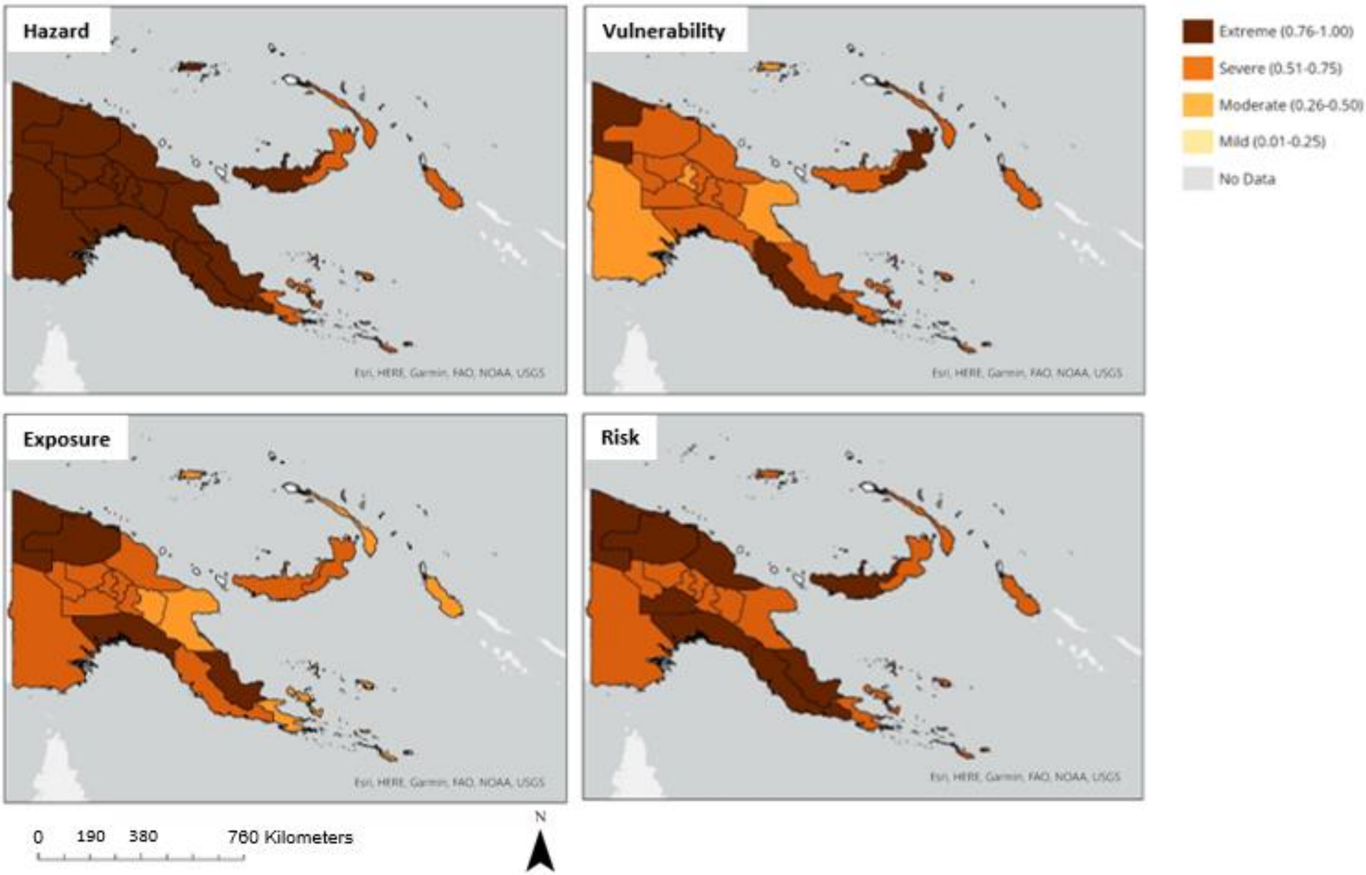
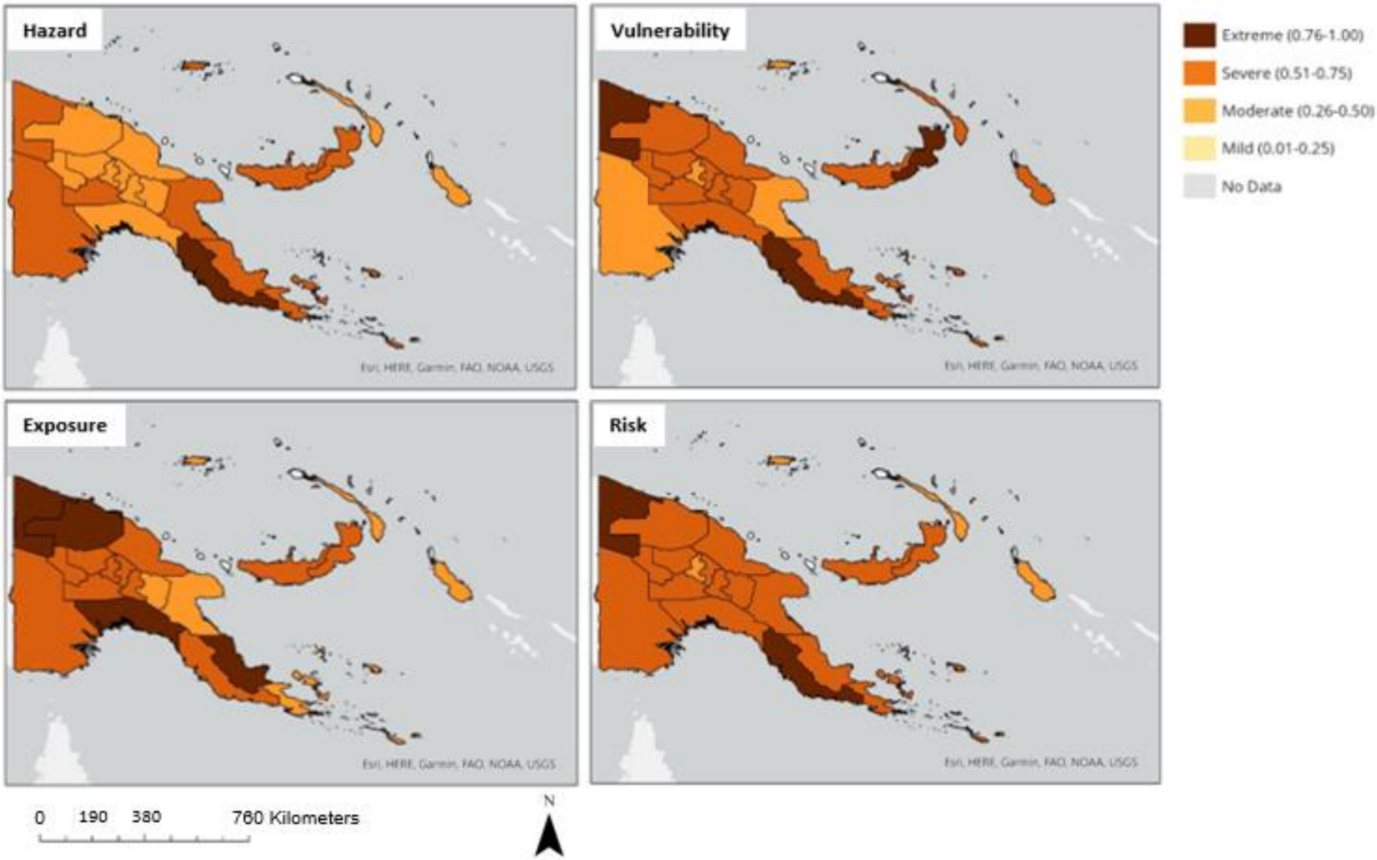


Figure 7. Overall drought risk maps of PNG provinces for 2015 including a drought hazard, drought vulnerability, drought exposure and drought risk map detailing the index level of each province. The index level is classified on a deepening orange colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00).



1055 Figure 8. 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).

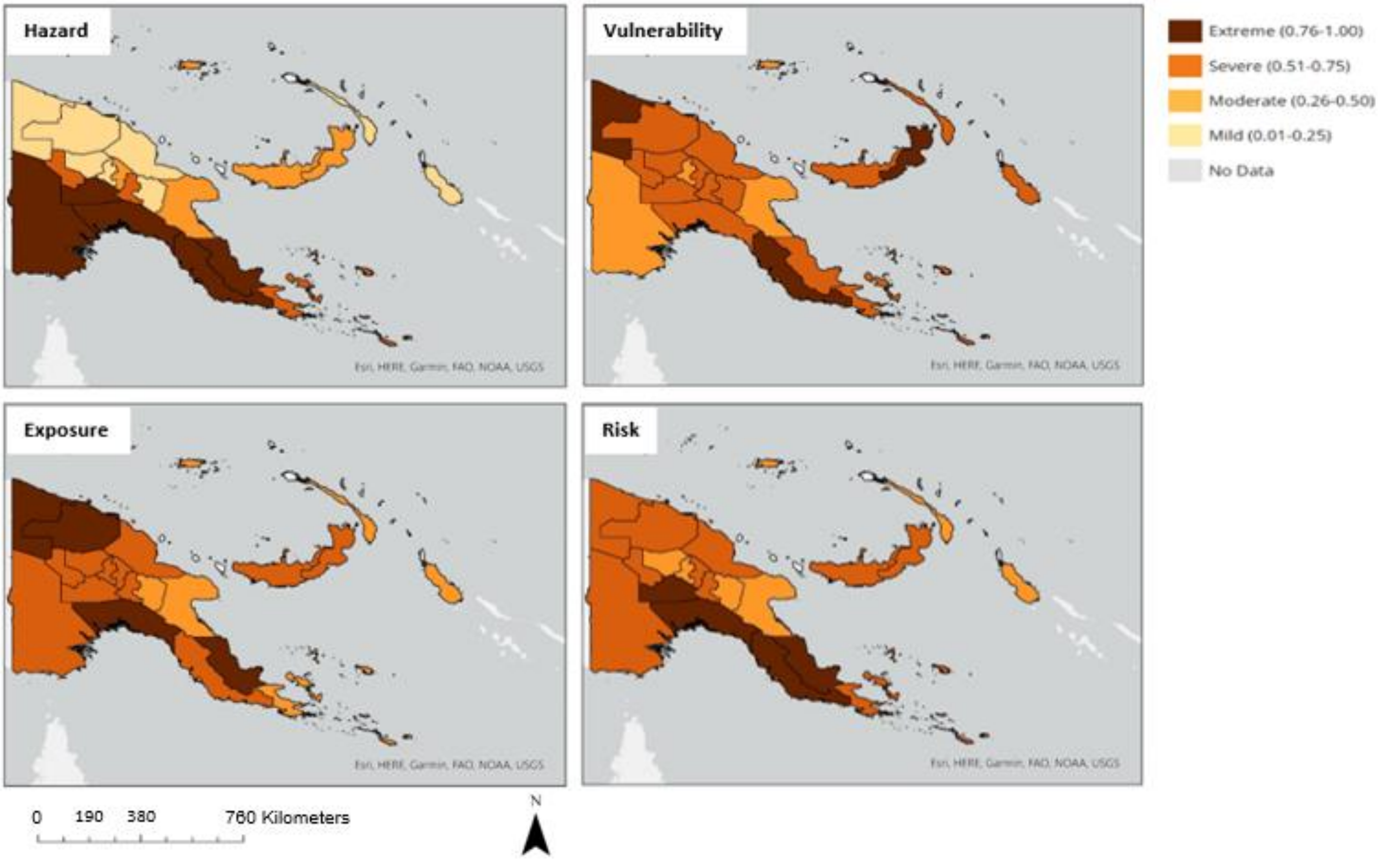


Figure 9. Overall Drought Risk Maps of PNG Provinces for 2019 including a Drought Hazard, Drought Vulnerability, Drought Exposure and Drought Risk Map detailing the index level of each province. The index level is classified on a deepening orange colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00).

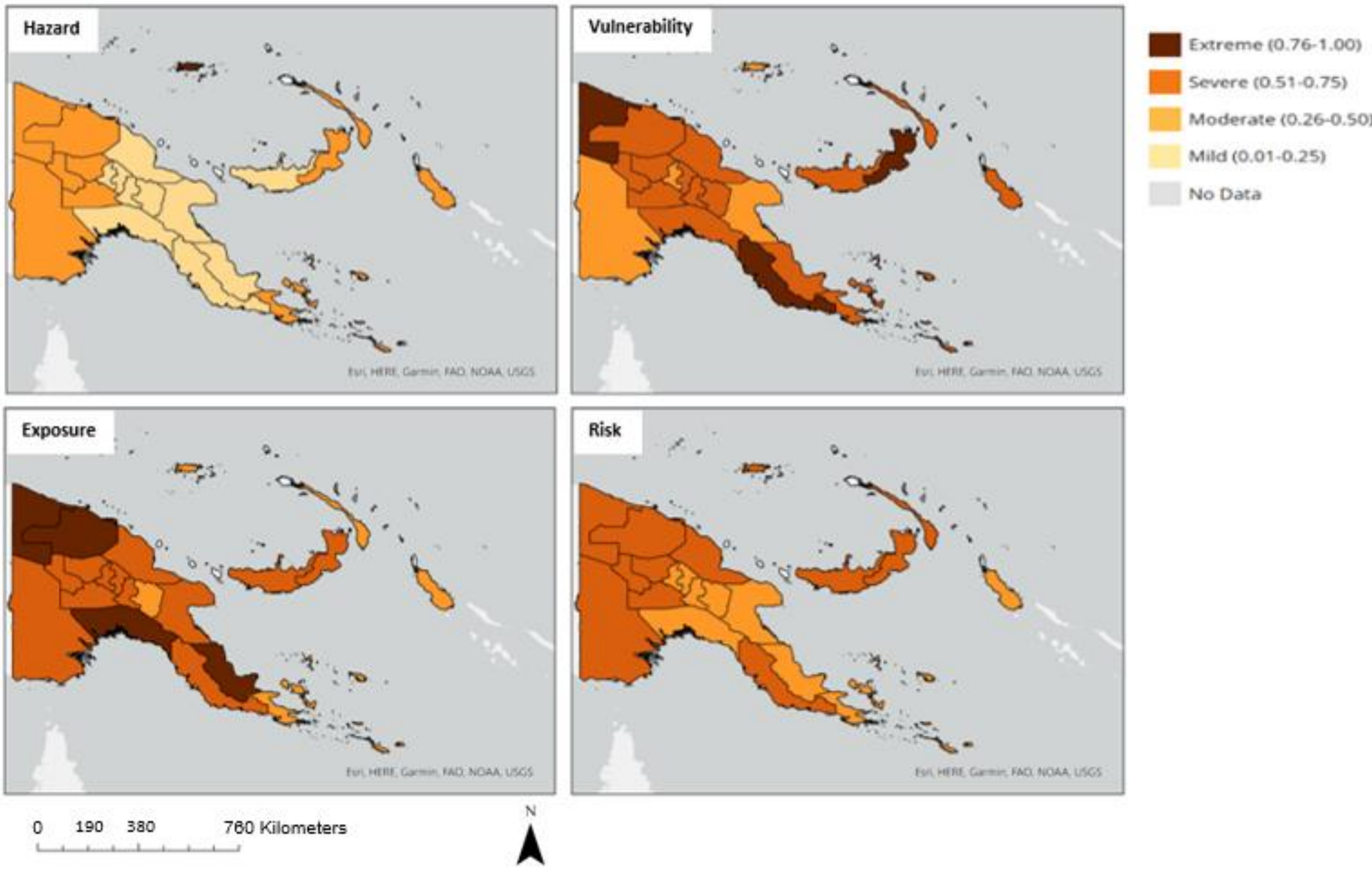


Figure 10. Overall Drought Risk Maps of PNG Provinces for 2020 including a Drought Hazard, Drought Vulnerability, Drought Exposure and Drought Risk Map detailing the index level of each province. The index level is classified on a deepening orange colour scale from Mild (index values from 0.01-0.25) to Extreme (index values from 0.76-1.00).

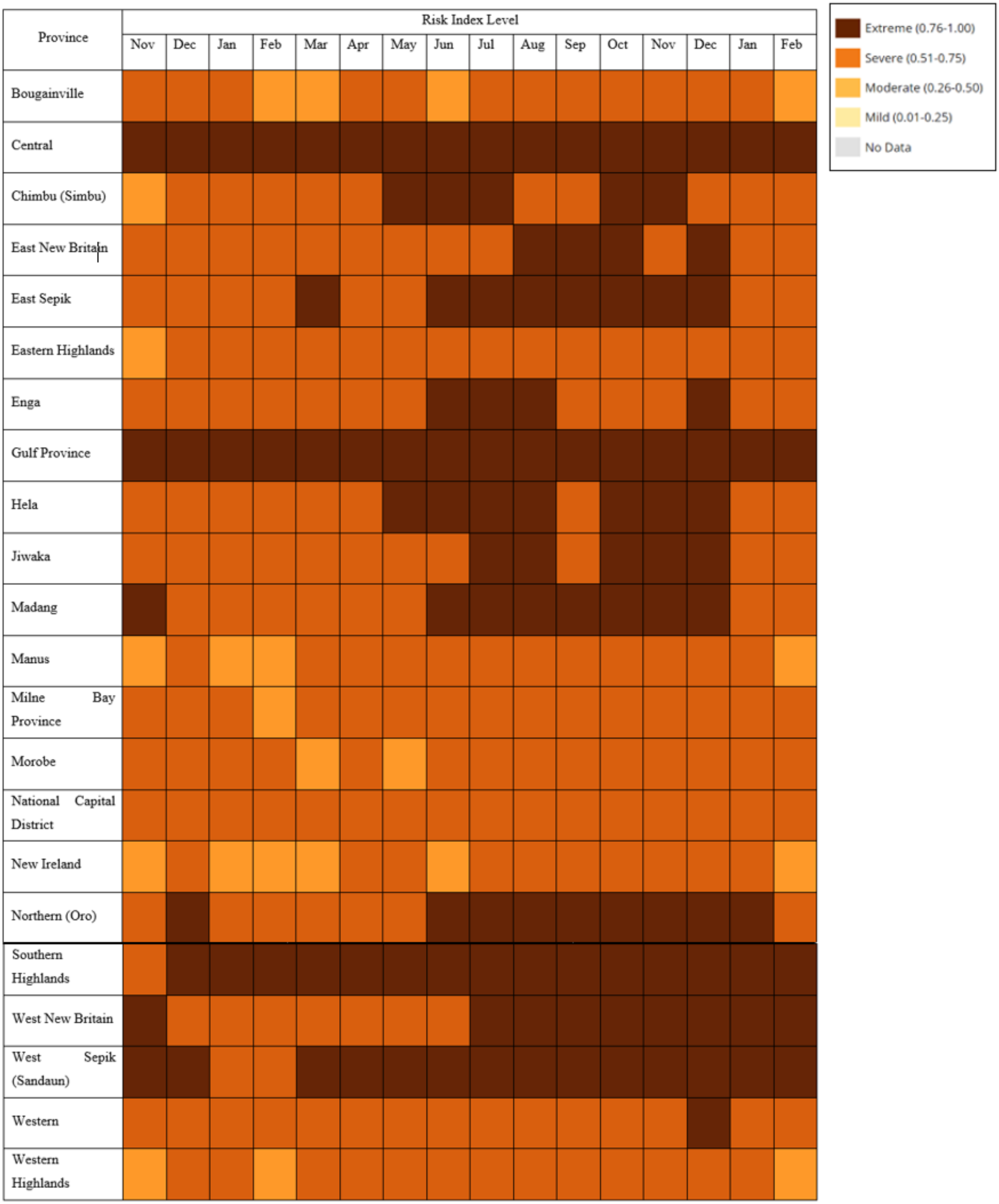

Province
Risk Index Level
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
Feb
Bougainville
Central
Chimbu (Simbu)
East New Britain
East Sepik
Eastern Highlands
Enga
Gulf Province
Hela
Jiwaka
Madang
Manus
Milne Bay Province
Morobe
National Capital District
New Ireland
Northern (Oro)
Southern Highlands
West New Britain
West Sepik (Sandaun)
Western
Western Highlands
Extreme (0.76-1.00)
Severe (0.51-0.75)
Moderate (0.26-0.50)
Mild (0.01-0.25)
No Data

Figure 11. 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 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).

Table 13. Average Sensitivity Index Values across PNG provinces for each indicator and the index which they inform using 2015 data as a case study. Rankings are shown for SI with highest sensitivity ranked first and lowest sensitivity ranked last. The likely credibility is also ranked amongst indicators, with first being the most credible for inclusion in the index and last being the least credible.

Index	Indicator	Sensitivity Index (Avg. across provinces)	Sensitivity Rank (highest to lowest SI)	Likely Credibility Rank
Hazard	SPI	0.56	1st	2nd
	VHI	0.47	2nd	1st
Vulnerability	Staple Crop Tolerance Score	0.41	1st	4th
	Agricultural Occupation	0.36	2nd	3rd
	Percentage of Children Weighed at Clinics Less than 80% Weight for Age 0 to 4 years old	0.33	3rd	2nd
	Key Crop Replacement Cost	0.31	4th	1st
Exposure	Land Use	0.39	1st	4th
	Elevation Type	0.34	2nd	3rd
	Population Density	0.32	3rd	2nd
	Access to Safe Drinking Water	0.31	4th	1st