Reviewer 1 comment: The introduction could be more concise. However, the specific goals of the study should be explained with more clarity therein.

I have cut down the introduction, specifically culling sections 1.1, 1.2, and 1.4. In 1.5 I have outlined the specific goals of the study more clearly. The paragraph below describes the specific goals of the study in a precise manner (it has been added as the final paragraph in section 1.5):

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 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.

Reviewer 1 comment: Limited room is given to results, whilst the discussion goes again in length, where it could be more concise (e.g. explanation of the 2014 anomaly).

The results have been populated with more content with the addition of a section on the selection of indicators and a section on a sensitivity analysis.

These sections are provided below:

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.

Tables are provided in the Supplementary Tables and Figures Document.

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.

Tables are provided in the Supplementary Tables and Figures Document.

Additionally, the discussion has been cut down. Specifically, section 4.3 has been removed, its content has been cut down and merged into section 4.1.

The following paragraph was added into section 4.1:

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.

Reviewer 1 comment: A problematic methodological choice is related to the very short "historical" period selected, of only seven years. The period should be extended to gather stronger evidence for the validity of the methodology.

We recognise that the historical period selected is limited. We are unable to extend the period beyond this currently, due to data limitations. However, to address this, the study period is now described as a ‘retrospective’ assessment period, rather than a ‘historical’ assessment period. Additionally, clear explanation has now been provided in section 4.6 in the discussion, which has been changed to a section called Study limitations and Further Research.

The following paragraph has been added to section 4.6 to discuss the limits of the short retrospective study period:

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).

Reviewer 1 comment: Especially with the impossibility of extending the period of analysis, a sensitivity analysis to enhance the evaluation and validity of the risk index is highly recommended

A sensitivity analysis was conducted and has been added into the paper to enhance the validation of the risk assessment.

A section on the sensitivity analysis methodology has been added to the methods section of the paper:

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 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).

A sensitivity analysis results section has been added into the results section of the paper:

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.

A sensitivity analysis discussion section has been added into the discussion section of the paper:

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.

Reviewer 1 comment: The paper starts highlighting SIDS as a special feature of the work, something that would give it added value, but in reality, it does not explicitly address SIDS, and the methodology could be assumed to be suitable for e.g. any inland continental area.

We have made more effort into highlighting the specific application of our research for Pacific SIDS throughout the paper. The following content has been added to emphasise the applicability of this research to Pacific SIDS specifically.

In 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.

In 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.

Reviewer 1 comment: In order to be used for I-EWS, risk analysis should ideally provide some predictive capability, but the methodology relies on data that are unable to provide that. Furthermore, the analysis at province level lacks resolution to be considered for a proper User centred I-EWS.

We see the risk assessment results informing an I-EWS. We intend the assessment to provide risk context for I-EWS warnings. The more predictive information would be provided by the I-EWS, and the risk assessment would frame the context in which warning information should be considered.

The limited ability of the risk assessment to predict drought events in recognised and a discussion paragraph has been added to section 4.5 Study limitations and further research:

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.

The collaborative process between an I-EWS and the risk assessment has now been more clearly outlined in the paper.

In section 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 (weeks, months, etc.), 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 paired with 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 user-centered I-EWS would be developed and used as ‘side-by-side’ products.

It is also recognised that the resolution of the assessment is not as localised as we would ideally want it, especially when considering its usability for an I-EWS. This limitation has now been clearly discussed in the paper.

In section 4.5 Study limitations and Further Research:

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.

Reviewer 1 comment: Results seems rather weak and the validity of the methodology for actual application at local level is not proved.

A sensitivity analysis has been added to the paper to enhance the insights able to be gained regarding validity of the risk assessment methodology.

In terms of application to the local level, the limitation of only conducting the risk assessment on the provincial level is recognised. Also, the usability for locals in PNG is considered, and a discussion point has been added to the paper regarding this.

The following content has been added to section 4.5 Study limitations and Further Research to address the usability of the risk assessment on a local level:

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.

Reviewer 1 comment: Line 1 (title and abstract): Most people outside Oceania will not get what PNG refers to. The use of acronyms in the title is not recommended, but if unavoidable at least in the abstract it should be explained.

PNG has been expanded to Papua New Guinea in the title.

Reviewer 1 comment: Line 35: please add a reference for the sentence

A reference (Kuleshov et al., 2014) has been added.

Reviewer 1 comment: 46-47: suitability is indicated as a key concept, but it is not explained well, I could not understand its definition from this sentence.

The definition provided has been revised. A clearer definition has been added to section 1.1:

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).

Reviewer 1 comment: 61: the four components seem actually five?

Communication and dissemination are one component (as stated by the World Meteorological Organisation in *Multi-Hazard Early Warning Systems: A Checklist*). Thus, there is four components: 1. Risk Knowledge 2. Warning Service 3. Communication and Dissemination 4. Response Capability.

Reviewer 1 comment: 68-70: a citation could be useful for this

A reference (Kuleshov et al., 2020) has been added.

Reviewer 1 comment: 119: what would be the most "efficient" methodology, what means efficiency in this context?

Further clarification of what the most efficient methodology looks like in this context has been added to section 1.3:

It is evident in the literature that the most efficient risk 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

[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.

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.

Reviewer 1 comment: 129: “preciseness of this method has been criticised” requires the reference to such criticism.

A reference (Fekete, 2019) has been provided for this sentence.

Reviewer 1 comment: 157: typo “scare” instead of “scarce”

This typo has been fixed.

Reviewer 1 comment: 201-209: the goals of the study are not very clear from this paragraph, which needs to be revised and rephrased, e.g. there is an apparent mixed use of “hazard” and “risk”, “hazard event” is unclear (line 204), it is a bit redundant, etc.

This paragraph has been revised, making sure to be clear about what the study intentions are and avoid redundancies. The language has also been rephrased to make sure that there is no confusion between the use of hazard, risk, and hazard event.

The revised paragraph is shown below:

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 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.

Reviewer 1 comment: 235: the range 2014-2020 seems very short and recent to be called “historical”

To avoid this problem, the word historical has now been replaced throughout the paper by the word retrospective. The historical risk assessment period is now referred to as a retrospective risk assessment period. A retrospective period is just a past period of time and does not assume a significant amount of time in the past, unlike a historical period.

Reviewer 1 comment: 247-250: The rationale for the selection of hazard, vulnerability and exposure indicators from the text and the appendix is not emerging properly. Whilst the availability of data is an unavoidable limiting factor, the combination of the indicators selected seems a rather “casual” one and replaceable in many ways. Therefore, a sounder justification and thorough explanation should be provided, or proper references, or, in the case the selection was data driven post-hoc, this should be stated and explained.

The selection process has been explained in more detail, and detailed tables have now been provided as part of the results to thoroughly explain why each indicator was selected, and why other possible indicators were omitted.

The selection process is described in more detail in the 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.

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 indicator variance was confirmed, raw data was uploaded to ArcGIS Pro.

The indicator selection results tables are included in the Supplementary Tables and Figures Document.

Reviewer 1 comment: 258: make sure to use "index" and "indicator" consistently and appropriately throughout the paper

We have gone through and have fixed up any instances in which these words have been used incorrectly and have now used each word in an appropriate and consistent manner to avoid confusion.

Reviewer 1 comment: 260: "historical and current" is not clear to what time range they actually refer to

We have now included the range in which each of these words refers to after each word when they are first introduced in the methodology: retrospective (2014-2019) and current (2020) data.

Reviewer 1 comment: 263-265: The choice of VHI is limiting the time span of analysis from 2014 onwards only, which is a drawback of this study. There are other products for vegetation with longer time series, why not using any of those? Especially because the weight given to VHI for hazard calculation is relatively small.

Further explanation as to why VHI is important for inclusion in the hazard index is provided in section 4.5 Study limitations and Further Research:

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).

Reviewer 1 comment: 283-284: "Thresholds […] were adapted" please add a bit more info on how they were adapted. Also, it states "Once indicator variance was confirmed", what does that mean?

This has been clarified with the addition of the following information in methodology part 1:

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.

Table 2 is provided in the Supplementary Tables and Figures Document.

Reviewer 1 comment: 294-295: the use of mean value from such a short "historical" time series to indicate the midpoint seems unreliable. Can you really state that is the best option?

This has now been clarified in the section methodology part 2:

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.

Reviewer 1 comment: 324: "Null 2021" is lacking from the references

Null 2021 has been added as a full reference, with further investigation into this reference revealing that it is better to list the author as Golden Gate Weather Services, 2021 in the reference list.

Reviewer 1 comment: 327: How is it formalized, the link between impacts reported by sources and the three severity classes?

This has now been clarified in the paper with the addition of the following information in methodology part 3:

Three severity levels were used to classify the strength of the events indicated in the assessment and literature: mild, moderate, and severe to extreme. 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.

Table 4 is provided in the Supplementary Tables and Figures Document.

Reviewer 1 comment: 335-338: what exactly are you testing statistically here? Cannot figure out

We understand that the way this part was written was unclear. We have now fixed this and have provided a clear explanation of what we were testing statistically in methodology part 3:

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[2]. 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

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[2] Statistical analyses were performed in Microsoft Excel.

(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 $\alpha = 0.05$.

Reviewer 1 comment: 340: It is not explained how the 3 levels of severity are translated into the 4 levels of risk used also by the assessment, for the comparison. Please clarify

This has been clarified in methodology part 3 with the addition of the following information.

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 3 is provided in the Supplementary Tables and Figures Document.

Reviewer 1 comment: 345-350: it is good and common practice to report the results of such tests in synoptic tables, whether in the main documents or in the annex.

Tables for the t-tests and f-tests have now been provided in the appendix. These tables are included in the supplementary tables and figures document.

Reviewer 1 comment: TABLE 2: no mild risk levels are displayed for any of the provinces in any year, basically. This is of concern, not just because it may diminish the informative value of the indicator, but especially because it looks like the risk has not been calibrated at its best. Now, it can be the case where calibration is fine, but the short range of years under analysis do not help to figure out, nor the risk components are presented separately to provide some hints (is it driven by hazard? Is it systematic high vulnerability? Etc.). Furthermore, given the somewhat arbitrary decisions taken to elaborate the risk index, a sensitivity analysis would enhance greatly the value of the results.

This result has been explained in the discussion section 4.1.

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**.**

A sensitivity analysis has also been provided to enhance the value of the results. The text describing the sensitivity analysis section in the paper has already been provided above.

Reviewer 1 comment: 354: rather moderate-severe, than mild-moderate, looking at the table.

This has been described as moderate in the paper (rather than moderate-severe or mild-moderate).

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).

Reviewer 1 comment: 405 and following: as stated also in the introduction, El Nino/Nina and IOD are indicated as drivers of drought in PNG, but they are completely ignored in the hazard component of the risk assessment. This should be explained or at least mentioned in the discussion.

These climate drivers have been mentioned in the discussion and specific reference is made to them when discussing the drought risk assessment results.

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).

ENSO phases are also referred to when discussing the hazard indicators SPI and VHI in the indicator selection table that has been added (Table 5):

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.

VHI is a spaced-based monitoring drought hazard indicator that can inform on whether an El Niño or La Niña event is occurring.

Reviewer 1 comment: 519-520: with indicators looking at 3 months cumulated values, it is unlikely that informative value would have been gathered enough in advance, as expected by an EWS. It is also probable that hazard variables may have sufficed in that regard, at province level.

This has now been addressed in section 4.5 Study limitations and Further Research. The following paragraph has been added to discuss this:

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.

Reviewer 1 comment: Figure 1 and 2: scale bar is lacking, please add

A scale has been added to Figure 1 and 2. See these updated figures in the supplementary tables and figures document.

Reviewer 1 comment: APPENDIX A: vegetation health index is indicated as meteorological indicator, but it is not. It is remote sensing and used for vegetation/agriculture. Access to safe drinking water is listed under Exposure, but it is unclear why, as well as Elevation

The VHI explanation has been fixed, it is not described as a meteorological indicator, rather 'VHI is a spaced-based monitoring drought hazard indicator'. Tables have been added to provide extensive information on the selection process for the hazard, vulnerability, and exposure indicators. In these tables, it is made clear why each of the selected indicators were chosen for use in this study.

The following information is provided in Table 9 for why Access to safe drinking water and Elevation have been chosen as exposure indicators:

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.

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., 2020b). 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, 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.

Reviewer 2 comment: New tools and techniques of data analysis and validation are not evident. Nor is there any innovative approach to data analysis.

The key innovation in this methodology is the combination of drought hazard, vulnerability, and exposure indices to formulate the drought risk index. Past studies commonly focus on hazard without inclusion of vulnerability and exposure, especially those conducted in Pacific SIDS. The consideration of all parts of an efficient risk assessment in our developed methodology is also novel (the risk assessment is dynamic (Hagenlocher et al., 2020), it is conducted on the most localised scale possible (Wilhelmi and Wilhite, 2002), is tailored[3] 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)); most previous studies only include one or two aspects of efficient risk assessment methodology (Hagenlocher et al. 2019). These points are now highlighted in the paper with the inclusion of the following content.

In methodology part 1 the following paragraph has been added:

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.

In section 4.6 the following sentence was added:

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.

Reviewer 2 comment: Much emphasis is placed on early warning systems, but it is not clear how this can be applied, validated, and implemented to these systems.

The use of the risk assessment to an early warning system is now explained more clearly in section 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,

[3] 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.

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 (weeks, months, etc.), 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 paired with 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 user-centered I-EWS would be developed and used as 'side-by-side' products.

Reviewer 2 comment: I also had some questions about how the authors reached some of their conclusions about the importance of individual indicators.

We have expanded on why each indicator was selected, how the weighting scheme was applied to each indicator, and by providing more detailed information on the selection rationale.

In methodology part 1 the following information has been added:

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.

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.

A paragraph has also been added to methodology part 2 elaborating on the weighting scheme applied to indicators:

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., 2020a; 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.

A section has also been added in the results to provide more detail on why each indicator was selected, and why certain potential indicators were not selected:

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.

Tables 5-10 are provided in the supplementary PDF.

Reviewer 2 comment: In that sense, the authors must elaborate more in the improvements that the proposed approach brings compared with the previous methodologies and what is the added value to their inclusion in EWS or to decision makers.

We have now elaborated on the key points which make this methodology novel and the improvements the proposed approach brings in comparison to previous methodologies, as well as the added value to EWSs and decision makers.

The importance of the risk assessment methodology developed here to early warning systems is further explained in section 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.).

A research significance section has also been added at the end of the paper, and merged with the conclusion to address the key points which make this methodology novel and the improvements the proposed approach brings in comparison to previous methodologies, as well as the added value to EWSs and decision makers:

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).

Reviewer 2 comment: The analysis presents two indicators that define droughts from a hazard point of view, but no definition of droughts is mentioned, please note that a drought indicator by itself does not define a drought event. For example, below what threshold of the indicators is considered the beginning of a dry period, when does a drought end, what is the minimum period that discriminates dry events from droughts, etc. What would happen if the anomalies of one indicator is positive and the other negative or if there is a time lag between precipitation anomalies and vegetation evidence (which is usually the case).

Drought risk, hazard, exposure, and vulnerability definitions have now been added to the methodology section part 1. Additionally, thresholds for each indicator, defining different strength of drought risk have now been added into a table in the methodology part 1. Additionally, the time lag between SPI and VHI has been addressed in methodology part 2.

In methodology part 1 the following information has been added to address this comment:

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).

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.

Table 2 is provided in the supplementary PDF.

In methodology part 2 the following information has been added to address this comment:

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.

Reviewer 2 comment: There is a difference between a "static" and a "dynamic" risk assessment. A static analysis identifies hotspots where adaptation or drought management measures should be implemented, and is usually based on a combination of a climatology of events over a reasonable period of time (e.g. exceedance probability or frequency of events), exposure and vulnerability, whereas a dynamic analysis aims to identify/highlight the possible impacts associated with observed events. This manuscript presents a "dynamic" risk analysis, which is correct in this context, but the theoretical framework and implications between a dynamic risk analysis and a static or baseline risk analysis have not been assessed, nor what the advantage of this is over a hazard-only monitoring system. In particular given that the risk indicator does not seem to fall below medium risk levels even in "non-dry periods".

Static and dynamic risk assessments are now introduced and defined, and the advantages of a dynamic risk assessment over a static one have been explained in the introduction section 1.3. The risk assessment we have developed is now mentioned as being dynamic in section 1.5 and 2.2.

In the introduction section 1.3 the following content has been added to address this comment:

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.

In the introduction section 1.5 the following content has been added to address this comment:

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.

In section 2.2 the following content has been added to address this comment:

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.

Additionally, the fact that the risk index does not commonly fall below moderate risk levels even in non-dry periods is addressed in the discussion section 4.1.

In section 4.1 the following content has been added to address this comment:

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**.**

References are made in many instances to implementation in I-EWS, but no explanation is given as to how this information can be used or implemented by such systems. Risk analysis is undoubtedly one of the fundamental pillars of any EWS, but certain important aspects need to be addressed. For example, how forecasts will be incorporated for early warning, which kind of models (dynamic or statistical modelling), on what timescale (days, weeks, months) and what is the skill of such forecasts.

A clearer explanation has been added to the paper regarding how risk information can be used or implemented by early warning systems.

The following explanation has been added to section 4.4 to address this comment:

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.

Reviewer 2 comment: I think this issue places a higher bar on the authors to be clearer about methodological choices, why some indicators were selected (sometimes only refers to the fact that they have been used in other similar regions, e.g. Appendix A), where there is missing data, and the spatial resolution and temporal coverage of the indicators that were chosen (e.g. the authors somewhere mention that data related to vulnerability were not available, this is reasonable, but it needs to be better elaborated). Taking into consideration the dynamics of societal vulnerability and economic indicators used might prevent decision makers to correctly interpret the results. All this information should be explicitly mentioned.

The reasoning behind indicator selection has been elaborated upon with the addition of detailed tables 5-10 in the results section of the paper.

These tables are provided in the supplementary PDF.

A comprehensive table detailing key indicator data information has been added. Table 1 includes information on the weights of each indicator, where the data is sourced from, when there is missing data and the spatial resolution and temporal coverage of each indicator.

Table 1 is included in the supplementary PDF.

Reviewer 2 comment: It seems that the decision on the selection of the proxy indicators relies mostly in the previous expert surveys, but further information on this is needed (e.g. references to the surveys, which other indicators were proposed, background of experts). A local level analysis should take advantage and propose a set of indicators really oriented to local vulnerability, main sectors affected by droughts and get to identify the root causes.

More detailed information on why each indicator was selected and why other potential indicators were omitted for this assessment is provided in Tables 5-10 as mentioned above.

These tables are provided in the supplementary PDF.

Additionally, it is important to note that this is a preliminary risk assessment methodology. It is intended that this methodology is to be improved upon in the future by increasing its user-centredness. In future investigation, surveys and interviews will be conducted to gain the perspective of locals regarding what vulnerability and exposure indicators are most appropriate for use. This feedback will inform further refinements of the PNG drought risk assessment, including the selection and weighting of indicators, given data is accurate and available. Currently, this task is beyond the scope of this research paper.

This point has been addressed in section 4.5 study limitations and further research:

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.

Reviewer 2 comment: In addition, no reference is made to the spatial resolution of the indicators (pixel, admin units, etc.) or how they were aggregated to regional scale (e.g. using average, median, mode, max, etc.). This is important information that could influence the results.

Table 1 has been added to the paper; it includes this information.

Table 1 is included in the supplementary PDF as mentioned above.

Reviewer 2 comment: There isn't really a thorough-going attempt to externally validate the map patterns in this paper. There is a comparison with literature, but this is not structured and it is hard to extract even a soft validation from this. A sensitivity analysis should test the decisions made in the construction of the combined indicator, like normalization and weighting schemes, sensitivity of adding or removing single proxy indicators, etc.

A sensitivity analysis has been conducted, the results of which have been added to the paper to clarify validation.

The sensitivity analysis method is described in 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 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).

The results of the sensitivity analysis are stated in section 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.

The sensitivity analysis results are discussed in section 4.3:

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.

Reviewer 2 comment: What about the years when the indicator gives medium/high risk (almost all) but no droughts have been observed? How is this to be understood? In page 12 the authors state that "The 2017 and 2018 drought risk assessments indicated most provinces as having mild or moderate drought risk levels, thus a drought event is not suspected, and these were likely non-drought years" How is a water manager or policy maker supposed to interpret this information?

Clarification has been added to section 4.1 on how to interpret such results:

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**.**

Reviewer 2 comment: ABSTRACT AND CONCLUSIONS- Both sections make broad and often unsubstantiated assertions in the manuscript. A revision of these two sections in line with the results obtained in this manuscript would be beneficial.

Both the abstract and conclusion have been revised in line with this comment.

The refined abstract is provided below:

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.

The conclusion was refined and combined with information on the significance of the results. The new concluding section is provided below:

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).

Reviewer 2 comment: INTRODUCTION- Introduction is too lengthy to discern the essence of the study. The most relevant part of this manuscript is section 1.5. Please consider focusing the introduction to this section.

The introduction has been culled, with sections 1.3 and 1.5 being the longest sections. It is believed that section 1.3 is also important to focus on as it introduces the key concept of disaster risk assessments and assesses the relevant methodologies that have been used in the past, concluding with a recommendation of the most efficient methodology which we have adapted for our research. The section 1.5 has remained a detailed and key section, as per the reviewer's recommendation.

The revised introduction is provided below:

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 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[4] 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.

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.

[4] 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.

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. Historically, the 1997-1998 El Niño contributed to severe drought in PNG causing immense loss of life, destruction of crops, and forest fires subsequently causing regional pollution problems (Nicholls, 2001). However, different regions of PNG experience varying climactic affects from El Niño and La Niña (Figure 1). For example, a moderate La Niña event which occurred in PNG during 2011-2012 resulted in drought conditions in several PNG provinces, particularly Milne Bay Province.

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

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

Generally, drought can be described as an extended dry period resulting from rainfall deficiency. However, drought has many definitions for its various types: meteorological (when climactic factors result in dry conditions within an area), hydrological (when water shortages occur after a period of meteorological drought), agricultural (when agricultural productivity is inhibited and crops are affected by meteorological and hydrological drought), and socioeconomic (when dry conditions restrict the supply and demand of commodities) (Wilhite et al., 2014). As drought impacts all major sectors (agriculture, economy, social, health, etc.), 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.

All figures referred to in this section have been provided in the supplementary PDF.

Reviewer 2 comment: METHODS- Methodology is mainly descriptive. Tools and techniques of data analysis are not explained. For example, the procedure adopted for generating maps of hazard, exposure, vulnerability and combining them to get drought risk needs to be better explained in the manuscript. As mentioned above, more information on how droughts are defined, selected indicators, temporal and spatial resolution, missing data, decisions taken to build the combined indicator, etc. should be detailed in this section.

The methodology section has been revised in line with the comment above. Effort has been taken to provide more detail throughout the methodology. Specifically, drought risk, hazard, vulnerability, and exposure definitions are provided, the indicator selection process is explained further and the key data information for each indicator is added in Table 1. The reasoning behind indicator selection was seen as more appropriate for the results section, so this information is provided int tables 5-10 in the results section of the paper.

The revised methodology section is provided below:

2. Data and Methodology

2.1 Study Area: PNG

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

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 (Figure 3) (Bhardwaj et al., 2021a). PNG climate also varies between years, with a dominant driver being ENSO (Figure 1).

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

Economic performance in PNG has historically been based on international prices for exports (including for agriculture), fiscal policies and construction activity. As of 2015, over 2 million Papua New Guineans are poor and/or face hardship, particularly those based in rural areas (Pacific Islands

Forum Secretariat, 2015). Agricultural occupation is consistently important for local livelihoods, with approximately 80-85% of the rural population directly deriving their livelihood from farming (Pacific Islands Forum Secretariat, 2015).

2.2 Study Design

The methodology 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[5] 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.

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[5] 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*[6] and *fuzzy large*[7]. *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[8]. 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., 2020a; 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.

The hazard, vulnerability and exposure indices were calculated using equations (1), (2) and (3), respectively for each province in the years and months under investigation.

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

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

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

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

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

$EI = \sum_{i=1}^{n}(w_i \, * \, x_i{}')$ (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., 2020a). 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 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; Null, 2021; Mckenna and Yakam, 2021; Food Security Cluster et al., 2021; 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[9]. 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 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

[9] Statistical analyses were performed in Microsoft Excel.

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).

All tables mentioned in this section are provided in the supplementary PDF.

APENDIX A, B and C, could be condensed in only one appendix (or even one table) as all of them shows different aspects of the same variables.

The appendix A, B and C have been combined into table 1 which is now included in the methodology section of the paper, rather than the appendix.

This table has been provided in the supplementary PDF.