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Reply on RC1

Isabella Aitkenhead et al.

Author comment on "Validating a tailored drought risk assessment methodology: drought risk assessment in local Papua New Guinea regions" by Isabella Aitkenhead et al., Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2021-278-AC1, 2022

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 5-10 are provided in the supplementary PDF.

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 16).

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 16).

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 16).

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.

Table 16 is provided in the supplementary PDF.

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 16).

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 16).

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 16).

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 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.

[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.

The indicator selection results tables (Tables 5-10) are included in the supplementary PDF.

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 PDF.

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 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 PDF.

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[1]. 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 $\alpha = 0.05$.

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).

[1] Statistical analyses were performed in Microsoft Excel.

Table 3 is provided in the supplementary PDF.

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.

Appendices A, B, C and D are provided in the supplementary PDF.

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 12), 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; Null, 2021; Papua New Guinea National Weather Service, 2020). Unlike the 2015-2016 drought event, drought conditions in PNG during 2019-2020 were due to a La Niña event. The second half of 2020 saw the emergence of a moderate to strong La Niña event that is causing extreme weather in many parts of the world. A neutral IOD phase was also evident, thus La Niña impacts were not exacerbated by the IOD. The impacts of La Niña on rainfall patterns vary across PNG. In the past, La Niña has resulted in wetter conditions over most of 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.

These updated figures are provided in the supplementary PDF.

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.

Please also note the supplement to this comment:
https://nhess.copernicus.org/preprints/nhess-2021-278/nhess-2021-278-AC1-supplement.pdf