Response to Editor

Comments to the author:

Dear Isabella Aitkenhead and co-authors,

Thank you for the submission of the revised version of your paper “Validating a Tailored Disaster Risk Assessment Methodology: Drought Risk Assessment in Local PNG Regions” to NHESS.

I asked two referees (a new one and one of the referees of the previous round) to provide detailed reviews. According to them the manuscript still requires several improvements. I agree with them, thus I recommended again “major revision”.

I would then like to invite you to submit a new revised version of your manuscript. As in the first round, reviewers’ concerns regards mostly the clarity of the methodology, its novelty aspects, as well as usefulness of obtained results, especially within the scope of EWSs. Another critical point is whether your methodology can be considered as static or dynamic. Please, pay attention to address all criticalities and comments raised by referees.

In addition to these, I strongly recommend you shortening the paper (at least of 30%) to increase its readability. There are many repetitions in the text, introduction can be shortened and make more tailored to drought risk, and you may consider to move some tables and figures in an electronic supplement.

Would you please also provide an ‘author’s reply’ to the reviewers and include a track changes document between the old manuscript and the new one (you can include this as part of your ‘author’s reply’).

I look forward to seeing the next version of your manuscript which I will then send out for further review to either the previous reviewers (if they agree) or new reviewers. I need to stress that this will be the last chance for improvement. If the new manuscript will still present major criticalities, I will stop the revision process.

Regards, D. Molinari

NHESS Editor

Author’s response:

Dear Dr Daniela Molinari,

Thank you for your Editor's comments. We have prepared a revised manuscript in response to both your comments and the reviewers' detailed comments. A document has been included detailing the authors reply to reviewers and a separate document highlighting all revisions using track changes is included. As there have been many changes, we recommend referring to the final revised version, without track changes.

Also please note that entire sections of the paper were re-written (like the results and discussion) to satisfy the reviewer comments, and to shorten the length of the paper.

Specifically, the paper has been shortened as best we can whilst still trying to incorporate all of the edits recommended by the reviewers.

We look forward to our further correspondence.

Kind Regards,

Yuriy Kuleshov and Isabella Aitkenhead

Corresponding authors

Authors Reply Round 2

Anonymous referee #3

Please see my general comments below and also more detailed in the commented PDF.

All detailed comments included in the PDF have been incorporated into the paper.

I was surprised by your strong focus on disaster risk analysis rather than drought risk analysis. Having in mind the work of Tanago Gonzales et al. 2016, Vogt et al. 2018, Hagenlocher et al. 2019, and Blauhut 2020 there is no actual need for not working with "disaster risk only". So your focus in the intro should be on drought?

This is correct and now the introduction has been amended accordingly. We have also considered the work of Tanago Gonzales et al. 2016, Hagenlocher et al. 2019, and Blauhut 2020. We refer to these publications throughout our paper as they are great references. Thank You for notifying us of their work.

Here, I also miss current research gaps in drought risk research that you want to fill. Many "research gaps" detected can be found in this reviews or more current research.

A section on the current research gaps for drought risk assessment on the global scale, as well as the PNG scale, has been added to the last section of the introduction:

1.5 Addressing drought risk assessment knowledge gaps in PNG

Generally, drought is insufficiently investigated on the global scale (Blauhut, 2020). Out of the few drought risk assessments previously conducted, most are lacking in effective methodological components (González Tánago et al. 2016). Blauhut (2020) recommends that future studies must "improve the characterisation of drought risks and its components" and "ascertain how this risk can be communicated…to enhance resilience to drought". Hagenlocher et al. (2019) corroborates that there are major gaps in previous risk assessment methodologies, like a lack of tailored indicator selection.

Tailored drought risk assessment is specific for measuring drought risk in a particular area and produces information for a certain set of stakeholders. This can be achieved by selecting hazard, vulnerability and exposure indices that specifically consider the climatic, socio-economic, and geographic characteristics of the area being assessed. Thus, generalised indicators would be omitted from the assessment. In recognising the importance of tailoring drought risk assessment through appropriate selection of indicators, Le et al. (2021) selected specific indicators for their agricultural drought risk assessment in Vietnam, based on three criteria (i) indicators are relevant to agricultural sector; (ii) data for these indicators are quantitative and publicly available, and (iii) indicators are specific to Vietnam's socio-economic conditions.

The scarce number of previous studies in PNG, assessing the risk of negative drought impacts, are commonly lacking in effective methodological aspects, and do not address key knowledge gaps in drought risk assessment investigation. An analysis of previous drought assessment studies in PNG is provided in table 1, and the methodological knowledge gaps are outlined. Overall, there is room for future investigation to develop a drought risk assessment to be utilised in PNG that incorporates the most effective methodological aspects, specifically considering the following: tailored and specific indicator selection; consistent drought risk *definitions; dynamic rather than static assessment; sufficient validation of indicators and results; and the provision of recommendations for risk reduction.*

Accordingly, this study will expand on previous research (Bhardwaj 2021b; Kuleshov 2020) with an aim to increase drought risk knowledge in PNG. Specifically, this research seeks to:

- *demonstrate the potential for tailored drought risk assessments to accurately inform on drought risk levels before, during and after a drought event and thus contribute to more resilient drought risk management in local areas, using drought in PNG as a case study.*

- *develop an effective, dynamic drought 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 development of the drought risk assessment is intended to aid the PNG NWS in informing local PNG stakeholders on which provinces are of highest concern and guide resilient drought risk management practices within priority communities.

Table 1. An analysis of previous drought assessment studies in PNG outlining the methodological aspects lacking.

Study source	Study Description	Effective Methodological Aspects Lacking
Korada et al. 2018	Performed in the Western Highlands province of PNG, which is a rain-fed subsistence farming dominated province highly vulnerable to drought, Korada et al. 2018 adopted GIS and remote sensing technology to highlight potential drought risk zones. General environmental indicators were used to inform the risk assessment: soil type, NDVI, rainfall, terrain, population demography and surface temperature. Using multi-criteria evaluation techniques in GIS, indicators were integrated, and risk areas were identified. Risk areas were mapped and then classified to indicate levels of drought risk from low, medium, and high.	Indicator selection is not specific and tailored; Risk assessment is static; Insufficient validation of indicators and results; Lacks the provision of recommendations for risk reduction; Lacks clear drought risk definitions.
Chua et al. 2020	Used remotely sensed indicators to assess drought over PNG. The indicators evaluated for this study included precipitation, vegetation health and soil moisture. Indicators were assessed on a monthly timescale from 2001 to 2018. A case study was then performed to determine the efficiency of such indicators to characterise drought in PNG during the 2015-2016 El Niño. This case study was used as a validation for indicator effectiveness in assessing drought impacts in PNG. It was found that Vegetation Health Index (VHI) and the Standardized Precipitation Index (SPI) were able to accurately indicate the spatial and temporal components of the 2015 to 2016 severe drought event in PNG caused by the El Niño phase. Overall, these satellite-derived precipitation products were recommended as potentially useful for operational use for drought detection and monitoring in PNG.	Inconsistent drought risk definitions: This is a hazard-centric assessment of drought impacts across PNG; The role of ecosystems and ecosystem services as a driver of risk is not explored.
Allen & Bourke 1997	An assessment of the risk of drought impacts was undertaken in response to the severe 1997-1998 El Nino induced drought in PNG. The impacts of the drought specifically on food supplies and water, on the national scale, were examined. Assessment teams, consisting of experts, were sent out to report on food supply conditions in rural communities, identify placed in severe need, assess migration out of impacted areas, assess local drinking water supply, assess health conditions, and report on the existence of emergency services and communications. Local people were interviewed and observed to obtain the information. Assessment teams each focused on specific area, provinces, or regions. The assessment was conducted over four weeks.	Inconsistent drought risk definitions: although vulnerability, exposure and hazard aspects of drought risk were considered in this study, no clear definitions were provided for drought risk; Lacks the provision of recommendations for risk reduction; No drought risk mapping was conducted; Risk assessment is static; Insufficient validation of indicators and results; Indicator selection is not specific and tailored: although a specific focus on food and water supply was employed, the assessment asked general questions about food and water supply and did not use specific indicators relevant to PNG.

Bang et al. 2003	Agricultural drought risk in PNG was assessed in response to the 2002 drought in PNG, using software developed by the Queensland Centre for Climate Applications. This software used correlations with the Southern Oscillation Index (SOI) and the Pacific Sea Surface Temperature (SST) to assess droughts. Overall drought risk in this study was classified as very low, low, moderate, high, and very high. Indicators considered for the agricultural drought assessment included: population density, slope of agricultural land, drought tolerance of crops, staple crop prevalence, altitude, reliance on agriculture, diversity of cropping systems, and use of irrigation systems, land use intensity, rainfall variability, precipitation deficiency and soil water deficiency. The assessment was carried out through surveys of local farming families residing in severely affected highland and lowland regions across PNG. The results of the study allowed for the following recommendation: a consistent implementation program of long-term farm-specific coping strategies is required in the vulnerable areas throughout PNG, particularly in the highland provinces.	Inconsistent drought risk definitions: although hazard, vulnerability and exposure indicators are considered, these components are not defined; Indicator selection is not specific and tailored: the selection process is not described in detail, with more focus given to the selection of assessed sites; Insufficient validation of indicators and results: no sensitivity analysis was performed to assess the robustness of indicators; No drought risk mapping was conducted.

We have also added more clarity in the concluding section of the paper, detailing how we have addressed the existing knowledge gaps in drought risk assessment for PNG:

In this study, an unprecedented attempt at developing a tailored drought risk assessment for the provincial scale across PNG was made. The development of a tailored, meaning highly specific to the area under investigation, drought risk assessment methodology has been recognised as vital to improving risk knowledge for the development of resilient drought risk management strategies in vulnerable communities (Wilhelmi and Wilhite 2002). Out of the disaster risk assessments that have been conducted in PNG, they have used arbitrary risk indicators (Bang et al., 2003; Allen & Bourke, 1997; Korada et al., 2018) and have been conducted on a broader (national/regional) level rather than local area (provinces) or community level (Hagenlocher et al. 2019). This research presents a methodology emphasising tailored risk assessment, with distinct criteria used to select suitable drought risk indicators. 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 and include local user consultation in the indicator selection process, however this is beyond the scope of the current research because of travel/resource limitations, and the remoteness of local PNG communities.

This study adopted the drought risk definitions consistent with those recommended by Hagenlocher et al. (2019). No such study has been conducted previously in PNG, where clearly defined hazard, vulnerability and exposure components are included to assess risk for all provinces. The assessment was intended to be dynamic, but limitations saw that it was only semi-dynamic. Due to data restrictions, the vulnerability and exposure components of the risk assessment consisted of annually updated, static indicators. Whereas the hazard component included dynamic factors. Thus, the approach is deemed a semi-dynamic drought risk assessment. For the assessment to become wholly dynamic, socio-economic data needs to become more readily available. The constrained availability of relevant, reliable, and updated data is recognised as majorly detrimental to drought risk assessments across the world (González Tánago et al. 2016). The semi-dynamic assessment can still provide important results, static assessment is useful for identifying where the origins and drivers of drought risk exist, and the areas that are of priority for long-term adaptation plans (Blauhut 2020, Hagenlocher et al., 2019 and González Tánago et al. 2016).

Indicators used and results produced underwent preliminary validation; however, a more comprehensive validation method is recommended for future research. The risk assessment methodology developed in this research was overall deemed valid. It provides the foundation for conducting drought risk assessments in PNG, to increase risk knowledge and inform local drought risk management. To consolidate this methodology as reliable in an operational sense, results must undergo validation against further ground-truth sources (e.g local accounts of past drought events). Results allowed for recommendation on disaster risk reduction in PNG, including the identification of priority areas that were detrimentally affected in previous drought, as well as recommendations for improved efficacy of the risk assessment methodology. This is a critical step commonly omitted from the risk assessment process ((Blauhut 2020, Hagenlocher et al., 2019 and González Tánago et al. 2016).

In the manuscript you also jump a lot between disaster risk and drought risk analysis. Please set your focus clear, you are doing a drought risk analysis.

This is very true. We have now fixed this and have made effort to consistently refer to drought risk assessment, rather than the more general ‘disaster risk assessment’ term.

The abstract and introduction has a very strong focus on early warning systems which is not really reflected in the paper.

To reduce the paper length, it was decided that EWS information was secondary to the risk assessment focus of the paper, and thus, the information produced on EWSs has been deleted.

On the other site, this study is on drought? But the introduction only gives VERY limited insights to the issues of drought in general (only 5 lines at the end). I therefore recommend to set a stronger and earlier focus on the topic! Drought risk is studies a lot, even though not well understood. Nevertheless, definitions for drought risk analysis and input data exists (e.g. static vs. dynamic, impact vs. conceptual, hybrid …..). Please check for the literature recommended. You might also check on Jackson 2001 (Jackson I 2001 Drought Hazard Assessment and Mapping for Antigua and Barbuda Available at: www.oas.org/pgdm/hazmap/drought/abdrttec.doc.) who investigated drought for small Caribbean islands

Effort has been made to revise the introduction, to primarily focus on drought in PNG from the start and clearly define drought and drought risk earlier in the introduction to set the scene for our study. The revised introduction is as follows:

1 Introduction

1.1 Drought in Papua New Guinea

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). Papua New Guinea (PNG) is one such country that has experienced destructive impacts from hazard events. In particular, drought has consistently devastated PNG communities in the past, and is predicted to increasingly affect PNG in the future (Kuleshov et al., 2014).

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 by meteorological and hydrological drought), and socioeconomic (when dry conditions restrict the supply and demand of commodities) (Wilhite et al., 2014). Drought events across PNG occur mainly a result of two key climate drivers: El Niño Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD).

In PNG, ENSO alters the distribution of precipitation, often causing precipitation extremes (Horton et al., 2021). ENSO has two key phases: El Niño (warm phase) and La Niña (cold phase). La Niña-associated prolonged rainfall has commonly contributed to floods, whilst El Niño-associated prolonged aridity has commonly contributed to droughts in PNG (Smith et al., 2013). Historically, the 1997-1998 El Niño contributed to severe drought in PNG causing immense loss of life, destruction of crops, and forest fires subsequently causing regional pollution problems (Nicholls, 2001). However, different regions of PNG experience varying climactic affects from El Niño and La Niña (Fig. 1). For example, a mild to moderate La Niña event which occurred in PNG during 2011-2012 resulted in drought conditions in several PNG provinces. Although in a La Niña phase, severe precipitation deficits were observed in New Ireland and Milne Bay Province throughout 2010 and the first half of 2011, resulting in drought conditions which contributed to crop destruction, food insecurity, and water shortages (Smith et al., 2013).

The effects of ENSO can be influenced by the IOD to further weaken or strengthen trends in rainfall variability (Bhardwaj et al., 2021b). Defined as consistent changes in sea surface temperature variability across the tropical western and eastern Indian Ocean, the IOD can be negative, positive, or neutral. Each IOD phase interacts with ENSO impacts differently (Bhardwaj et al., 2021b). The impacts of interactive IOD and ENSO phases experienced in PNG are shown in Fig. 2. Whilst drought conditions can occur in PNG in any ENSO or IOD phase, extreme drought conditions are most often a result of a positive IOD phase interacting with an El Niño ENSO phase.

1.2 Disaster risk reduction and resilient risk management of droughts in Papua New Guinea

PNG has a lack of coping capacity for managing the risks posed by the drought events which occur across the country, due to limited resource availability, including water and food insecurity, and reactive management practices (Kuleshov et al., 2020). Although drought historically has disastrous impacts on PNG communities, the risk of drought has not been extensively investigated compared to other hazards like tropical cyclones and floods. Due to the lack of drought risk knowledge, and the lack of coping capacity, future disaster risk reduction (DRR) of drought, through resilient drought risk management, is of priority in PNG (Bang and Crimp, 2019).

Resilient drought risk management consists of two key elements: proactivity and suitability. In this instance, proactivity is characterised by controlling a drought risk situation prior to the occurrence of a drought event, rather than responding to drought after it has reached a crisis level. Suitability is seen as the level of appropriateness that drought management strategies have for application at localised levels in vulnerable places. A drought 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 drought resilience in PNG, the proactivity and suitability of localised disaster risk management is of critical focus (Mercer, 2010).

1.2 Investigating drought risk knowledge in PNG: Drought risk assessments

Drought risk assessments are increasingly recognised as key to informing proactive and suitable drought risk management decisions, as they aid in increasing risk knowledge and can identify priority management areas. Such assessments are commonly used in global studies investigating drought risk knowledge, and there is potential for application of these assessments in SIDSs like PNG (Chen et al., 2003; Rahmati et al., 2020). Drought risk assessments analyse the risk of adverse drought impacts in a particular area. Drought risk is defined as the probability of harmful consequences, or expected losses resulting from interactions between drought hazard (the possible future occurrence of drought hazard events); drought exposure (the total population, its livelihoods and assets in an area in which drought hazard events may occur); and drought vulnerability (the tendency of exposed factors to suffer negative impacts when drought hazard events occur) (Sharafi et al., 2020).

It is widely accepted that there are two types of risk assessments: static and dynamic. Dynamic drought risk assessments consider both the spatial and temporal aspects of droughts, using historic, periodically updated, and simulated data. Additionally, dynamic assessments incorporate not only hazard monitoring indicators, but also vulnerability and exposure indicators (Mosquera-Machado and Dilley, 2009). Most drought risk assessments that have been previously conducted have been static assessments (Hagenlocher et al., 2020). 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 drought risk; drought risk is not static, but rather dynamic in both space and time (Hagenlocher et al., 2020).

The vitality of such dynamic drought 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 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. Fuzzy logic is a data transformation and standardisation technique increasingly recognised as useful in drought risk mapping (Dayal et al., 2018). As drought risk is dynamic, assessing and mitigating regional drought impacts is likely to involve some level of subjectivity as there are no standard criteria on mapping and quantifying drought risk. The application of fuzzy logic in GIS, minimises the subjectivity in drought risk assessment, thus improving the efficiency of risk assessment as a tool for spatial decision-making (Dayal et al., 2018). 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 (Blauhut, 2020).*

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

Drought risk assessments commonly lack adequate validation (Asare-Kyei et al., 2017; Blauhut 2020). In a review of past 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 (González Tánago et al. 2016).

Validation through result comparison with historical data has been used in several studies (Wu and Wilhite, 2004), however the preciseness of this method has been criticised (Fekete, 2019). Molinari et al. (2019) states 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. A ground-truth source provides information that is real or true, given by direct observation or measurement in the real world. For example, drought impact records for a particular event provided by locals who experienced the event first-hand.

Participatory research is a technique which 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, some past investigations using this method have employed an additional 'ground-truth' source to strengthen validation adequacy (González Tánago et al. 2016). For example, Bijaber (2018) verified risk assessment results with historical on-the-ground precipitation and crop data at the national scale in Morocco, as well as the views of experts regarding what conditions were experienced during the study period.

In addition to validating risk assessment results, a statistical sensitivity analysis is also recommended as best practice for validating the selection of drought risk indicators informing the risk assessment (Hangelocher et al., 2019). Sensitivity analysis is used to determine how different values of an independent variable affect a particular dependent variable under a provided set of assumptions. Although recognised as a critical verification tool, previous drought risk assessment studies commonly exclude sensitivity analysis. In a review of past drought risk assessments, Hangelocher et al. (2019) determined that only 12% of studies conducted a statistical sensitivity analysis, with only four studies employing both a validation of risk assessment outcomes against a ground-truth source and a sensitivity analysis.

In Pacific SIDS like PNG, data availability is scarce. Therefore, validation through comparison with historical independent data is unlikely to be credible. Overall, a strengthened validation methodology using multiple ground-truth sources, and an additional sensitivity analysis, seems most promising for future study of drought risk assessments in PNG.

1.5 Addressing drought risk assessment knowledge gaps in PNG

Generally, drought is insufficiently investigated on the global scale (Blauhut, 2020). Out of the few drought risk assessments previously conducted, most are lacking in effective methodological components (González Tánago et al. 2016). Blauhut (2020) recommends that future studies must "improve the characterisation of drought risks and its components" and "ascertain how this risk can be communicated…to enhance resilience to drought". Hagenlocher et al. (2019) corroborates that there are major gaps in previous risk assessment methodologies, like a lack of tailored indicator selection.

Tailored drought risk assessment is specific for measuring drought risk in a particular area and produces information for a certain set of stakeholders. This can be achieved by selecting hazard, vulnerability and exposure indices that specifically consider the climatic, socio-economic, and geographic characteristics of the area being assessed. Thus, generalised indicators would be omitted from the assessment. In recognising the importance of tailoring drought risk assessment through appropriate selection of indicators, Le et al. (2021) selected specific indicators for their agricultural drought risk assessment in Vietnam, based on three criteria (i) *indicators are relevant to agricultural sector; (ii) data for these indicators are quantitative and publicly available, and (iii) indicators are specific to Vietnam's socio-economic conditions.*

The scarce number of previous studies in PNG, assessing the risk of negative drought impacts, are commonly lacking in effective methodological aspects, and do not address key knowledge gaps in drought risk assessment investigation. An analysis of previous drought assessment studies in PNG is provided in table 1, and the methodological knowledge gaps are outlined. Overall, there is room for future investigation to develop a drought risk assessment to be utilised in PNG that incorporates the most effective methodological aspects, specifically considering the following: tailored and specific indicator selection; consistent drought risk definitions; dynamic rather than static assessment; sufficient validation of indicators and results; and the provision of recommendations for risk reduction.

Accordingly, this study will expand on previous research (Bhardwaj 2021b; Kuleshov 2020) with an aim to increase drought risk knowledge in PNG. Specifically, this research seeks to:

- *demonstrate the potential for tailored drought risk assessments to accurately inform on drought risk levels before, during and after a drought event and thus contribute to more resilient drought risk management in local areas, using drought in PNG as a case study.*

- *develop an effective, dynamic drought 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 development of the drought risk assessment is intended to aid the PNG NWS in informing local PNG stakeholders on which provinces are of highest concern and guide resilient drought risk management practices within priority communities.

The entire study is highlighted as tailored risk analysis. This sounds good, but you did not manage to explain why your approach is tailored, and other approaches do not. All indices are chosen arbitrary and than combined equally. This is not tailored (for PNG) at all rather than picking up on the classic of drought risk analysis of the past.

The indicators are not combined equally, they are combined using a weighted approach. An expert weighting scheme is employed to weight each indicator in each of the indices. The hazard, vulnerability and exposure indices are then combined equally to produce the risk index. The hazard, vulnerability and exposure indices are equally important components of drought risk; therefore, they are combined equally to calculate the drought risk index. This is all explained in section 2.2.2 Methodology: Part 2:

To calculate the hazard, vulnerability, and exposure indices, indicator data was first reclassified by a linear function (using the rescale by function tool in ArcGIS Pro) 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 (Equation 1).

$$\mu A(x): X \longrightarrow [0,1] \qquad (1)$$

where $\mu A(x)$ refers to the grade of membership for element x in a fuzzy set A, and the X is the universal set.

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 and fuzzy large . 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.

In fuzzy large, larger inputs have membership values closer to 1. This function is defined by a midpoint value that can be left as a default or manually adjusted to suit specific datasets, which is assigned a membership of 0.5. Equation 2 gives the mathematical expression for fuzzy large membership.

$$\mu(x) = 1/(1 + (x/f2)^{(-f1)}) \tag{2}$$

where f1 is the spread and f2 is the assigned midpoint.

In fuzzy small, smaller inputs have membership values closer to 1. Like fuzzy large, it is defined by a either a default or manually assigned midpoint that is given a membership value of 0.5. Equation 3 gives the mathematical expression for fuzzy small membership.

$$\mu(x) = 1/(1 + (x/f2)^{f1}) \tag{3}$$

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 . Thus, a 2014, 2015, 2016, 2017, 2018, 2019, and 2020 standardised raster layer was mapped on the provincial scale for each of the ten indicators. This was also done for the months investigated as part of the 2015 case study. After standardising indicator data, numerical weights were assigned by researchers to each indicator based on an expert weighting scheme informed by past studies and advice from the PNG NWS. The weights assigned reflected the relative importance and contribution of each indicator to the specific index it informs. This weighting scheme was on a 0-1 scale, with 0 indicating no probable contribution to the relative index and 1 being total probable contribution to the relative index (Frischen et al., 2020). The weights assigned to each hazard, vulnerability and exposure indicator are shown in table 2.

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 (Zhao et al. 2022). Additionally, VHI primarily signals only agricultural drought, whereas SPI considers multiple drought types (meteorological, hydrological, and agricultural). So, in a holistic drought risk assessment aiming to encompass all forms of drought, as in this study, SPI could be weighted more.

The vulnerability, hazard and exposure indices were calculated for each province, and spatial maps of the area covering the 22 provinces of PNG (representing vulnerability, exposure, and hazard per unit area) were produced, through the raster calculator in ArcGIS Pro using Equations 4, 5, and 6 (Dayal et al., 2018). Vulnerability, hazard and exposure indices were calculated for each year and month under investigation.

$$HI = \sum_{i=1}^{n} (w_i * x_i') \tag{4},$$

$$VI = \sum_{i=1}^{n} (w_i * x_i') \tag{5},$$

$$EI = \sum_{i=1}^{n} (w_i * x_i') \tag{6},$$

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, xi' refers to the standardised indicators and wi refers to the respective indicator weight.

The final drought risk index value for each PNG province was then determined and mapped 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. The mathematical expression for this function is given in Equation 7 (Dayal et al., 2018).

$$\mu_{gamma} = (\mu_{sum})^{\gamma} \times (\mu_{product})^{(1-\gamma)} \tag{7}$$

where μgamma is the calculated fuzzy membership function, γ is a parameter chosen between 0 and 1; μsum is the fuzzy algebraic SUM and μproduct is the fuzzy algebraic PRODUCT that is mathematically expressed in Equation 8 and 9 respectively (Dayal et al., 2018).

$$\mu_{sum} = 1 - \prod_{i=1}^{n} (1 - \mu_i) \tag{8},$$

$$\mu_{product} = 1 - \prod_{i=1}^{n} (\mu_i) \qquad (9)$$

where μi is the fuzzy membership for the map, and i equals the number of maps to be combined. In the fuzzy gamma operation, γ=0 is equivalent to the fuzzy product and γ=1 is equivalent to fuzzy sum.

Once a final drought risk map was produced for each year and month under investigation, the extent of drought risk displayed was classified into five levels: very mild (0.01 to 0.20 index values, mild (0.21 to 0.40 index values), moderate (0.41 to 0.60 index values), severe (0.61 to 0.80 index values), and extreme (0.81 to 1.00 index values). These classifications are commonly used in drought risk assessments (Dayal et al., 2018; Frischen et al., 2020).

We have added clear explanation of what a tailored risk assessment is and why our approach is tailored. Explanation is also provided for why this makes our research innovative. The following information has been added to the introduction, methods, and discussion.

In section 1.5 Addressing drought risk assessment knowledge gaps in PNG:

Hagenlocher et al. (2019) corroborates that there are major gaps in previous risk assessment methodologies, like a lack of tailored indicator selection.

Tailored drought risk assessment is specific for measuring drought risk in a particular area and produces information for a certain set of stakeholders. This can be achieved by selecting hazard, vulnerability and exposure indices that specifically consider the climatic, socio-economic, and geographic characteristics of the area being assessed. Thus, generalised indicators would be omitted from the assessment. In recognising the importance of tailoring drought risk assessment through appropriate selection of indicators, Le et al. (2021) selected specific indicators for their agricultural drought risk assessment in Vietnam, based on three criteria (i) indicators are relevant to agricultural sector; (ii) data for these indicators are quantitative and publicly available, and (iii) indicators are specific to Vietnam's socio-economic conditions.

In Table 1, when reviewing methodological gaps from pervious PNG drought risk assessments, it is highlighted that indicator selection is commonly not specific and tailored:

Table 1. An analysis of previous drought assessment studies in PNG outlining the methodological aspects lacking.

Study source	Study Description	Effective Methodological Aspects Lacking
Korada et al. 2018	Performed in the Western Highlands province of PNG, which is a rain-fed subsistence farming dominated province highly vulnerable to drought, Korada et al. 2018 adopted GIS and remote sensing technology to highlight potential drought risk zones. General environmental indicators were used to inform the risk assessment: soil type, NDVI, rainfall, terrain, population demography and surface temperature. Using multi-criteria evaluation techniques in GIS, indicators were integrated, and risk areas were identified. Risk areas were mapped and then classified to indicate levels of drought risk from low, medium, and high.	Indicator selection is not specific and tailored; Risk assessment is static; Insufficient validation of indicators ar results; Lacks the provision of recommendations for risk reduction; Lacks clear drought risk definitions.
Chua et al. 2020	Used remotely sensed indicators to assess drought over PNG. The indicators evaluated for this study included precipitation, vegetation health and soil moisture. Indicators were assessed on a monthly timescale from 2001 to 2018. A case study was then performed to determine the efficiency of such indicators to characterise drought in PNG during the 2015-2016 El Niño. This case study was used as a validation for indicator effectiveness in assessing drought impacts in PNG. It was found that Vegetation Health Index (VHI) and the Standardized Precipitation Index (SPI) were able to accurately indicate the spatial and temporal components of the 2015 to 2016 severe drought event in PNG caused by the El Niño phase. Overall, these satellite-derived precipitation products were recommended as potentially useful for operational use for drought detection and monitoring in PNG.	Inconsistent drought risk definitions: This is a hazard-centric assessment o drought impacts across PNG; The role of ecosystems and ecosystem service as a driver of risk is not explored.
Allen & Bourke 1997	An assessment of the risk of drought impacts was undertaken in response to the severe 1997-1998 El Nino induced drought in PNG. The impacts of the drought specifically on food supplies and water, on the national scale, were examined. Assessment teams, consisting of experts, were sent out to report on food supply conditions in rural communities, identify placed in severe need, assess migration out of impacted areas, assess local drinking water supply, assess health conditions, and report on the existence of emergency services and communications. Local people were interviewed and observed to obtain the information.	Inconsistent drought risk definitions: although vulnerability, exposure and hazard aspects of drought risk were considered in this study, no clear definitions were provided for drough risk; Lacks the provision of recommendations for risk reduction;

	Assessment teams each focused on specific area, provinces, or regions. The assessment was conducted over four weeks.	No drought risk mapping was conducted; Risk assessment is static; Insufficient validation of indicators ar results; Indicator selection is not specific and tailored: although a specific focus on food and water supp was employed, the assessment asked general questions about food and water supply and did not use specific indicators relevant to PNG.
Bang et al. 2003	Agricultural drought risk in PNG was assessed in response to the 2002 drought in PNG, using software developed by the Queensland Centre for Climate Applications. This software used correlations with the Southern Oscillation Index (SOI) and the Pacific Sea Surface Temperature (SST) to assess droughts. Overall drought risk in this study was classified as very low, low, moderate, high, and very high. Indicators considered for the agricultural drought assessment included: population density, slope of agricultural land, drought tolerance of crops, staple crop prevalence, altitude, reliance on agriculture, diversity of cropping systems, and use of irrigation systems, land use intensity, rainfall variability, precipitation deficiency and soil water deficiency. The assessment was carried out through surveys of local farming families residing in severely affected highland and lowland regions across PNG. The results of the study allowed for the following recommendation: a consistent implementation program of long-term farm-specific coping strategies is required in the vulnerable areas throughout PNG, particularly in the highland provinces.	Inconsistent drought risk definitions: although hazard, vulnerability and exposure indicators are considered, these components are not defined; Indicator selection is not specific and tailored: the selection process is not described in detail, with more focus given to the selection of assessed site Insufficient validation of indicators ar results: no sensitivity analysis was performed to assess the robustness o indicators; No drought risk mapping was conducted.

The following text was added to section 2.2.1 Methodology: Part 1:

Tailored risk indicators were selected for monitoring drought risk in PNG on the provincial scale, based on the following criteria adapted from Le et al. (2021) (i) indicators are relevant to one or more of the three most drought impacted sectors in PNG (economic sector, agricultural sector, and health sector) (ii) data for these indicators are quantitative and publicly available, and (iii) hazard indicators are highly specific to PNG's climactic conditions and the vulnerability and exposure indicators are highly specific to PNG's socioeconomic and geographic conditions. An analysis of indicator selection in earlier studies of characteristically similar areas to the 22 provinces of PNG was used to measure the suitability of potential indicators for this study against the selection criteria described above. PNG National Weather Service (NWS) advice was also sought to approve indicator selection for this study. Additionally, hazard indicators were assessed against recommendations made by WMO in their Handbook of Drought Indicators and Indices (Svoboda and Fuchs, 2016).

It is important to note that:

- *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), and each major sector experiencing the effects (Bhardwaj et al., 2021b).*

- *publicly accessible 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.*

Additional information can now be found in section 4.5.1 Indicator Selection Process:

In the literature, it is indicated that current practice for indicator selection is to select indicators based on a review of literature (Frischen et al., 2020) and use of current expert knowledge (Dayal et al., 2018). Indicators are commonly arbitrarily selected for the country they are to be used to assess. It is common for data restrictions to be a limiting factor of indicator selection (Dayal et al., 2018). As this study seeks to select specifically suitable indicators for assessment of drought risk on a more localised scale in PNG, to achieve a tailored drought risk assessment, it would have been ideal to select indicators not only based on a literature review or current expert knowledge, but also established with local knowledge 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 following has also been added to the discussion section 4.6 Research Significance and Conclusions:

In this study, an unprecedented attempt at developing a tailored drought risk assessment for the provincial scale across PNG was made. The development of a tailored, meaning highly specific to the area under investigation, drought risk assessment methodology has been recognised as vital to improving risk knowledge for the development of resilient drought risk management strategies in vulnerable communities (Wilhelmi and Wilhite 2002). Out of the disaster risk assessments that have been conducted in PNG, they have used arbitrary risk indicators (Bang et al., 2003; Allen & Bourke, 1997; Korada et al., 2018) and have been conducted on a broader (national/regional) level rather than local area (provinces) or community level (Hagenlocher et al. 2019). This research presents a methodology emphasising tailored risk assessment, with distinct criteria used to select suitable drought risk indicators. 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 and include local user consultation in the indicator selection process, however this is beyond the scope of the current research because of travel/resource limitations, and the remoteness of local PNG communities.

Thus, I please you to "sell" your novel (?) product better and explore your added value in contrast to the current state of the art.

Information has been added to the introduction to explain the usefulness of our research in the context of the current state of drought risk assessment, particularly for those conducted for PNG. The methodological knowledge gaps of previous risk assessment are highlighted, and these are the gaps our assessment intends to address.

The following information was added to the introduction:

1.5 Addressing drought risk assessment knowledge gaps in PNG

Generally, drought is insufficiently investigated on the global scale (Blauhut, 2020). Out of the few drought risk assessments previously conducted, most are lacking in effective methodological components (González Tánago et al. 2016). Blauhut (2020) recommends that future studies must "improve the characterisation of drought risks and its components" and "ascertain how this risk can be communicated…to enhance resilience to drought". Hagenlocher et al. (2019) corroborates that there are major gaps in previous risk assessment methodologies, like a lack of tailored indicator selection.

Tailored drought risk assessment is specific for measuring drought risk in a particular area and produces information for a certain set of stakeholders. This can be achieved by selecting hazard, vulnerability and exposure indices that specifically consider the climatic, socio-economic, and geographic characteristics of the area being assessed. Thus, generalised indicators would be omitted from the assessment. In recognising the importance of tailoring drought risk assessment through appropriate selection of indicators, Le et al. (2021) selected specific indicators for their agricultural drought risk assessment in Vietnam, based on three criteria (i) indicators are relevant to agricultural sector; (ii) data for these indicators are quantitative and publicly available, and (iii) indicators are specific to Vietnam's socio-economic conditions.

The scarce number of previous studies in PNG, assessing the risk of negative drought impacts, are commonly lacking in effective methodological aspects, and do not address key knowledge gaps in drought risk assessment investigation. An analysis of previous drought assessment studies in PNG is provided in table 1, and the methodological knowledge gaps are outlined. Overall, there is room for future investigation to develop a drought risk assessment to be utilised in PNG that incorporates the most effective methodological aspects, specifically considering the following: tailored and specific indicator selection; consistent drought risk definitions; dynamic rather than static assessment; sufficient validation of indicators and results; and the provision of recommendations for risk reduction.

Accordingly, this study will expand on previous research (Bhardwaj 2021b; Kuleshov 2020) with an aim to increase drought risk knowledge in PNG. Specifically, this research seeks to:

- *demonstrate the potential for tailored drought risk assessments to accurately inform on drought risk levels before, during and after a drought event and thus contribute to more resilient drought risk management in local areas, using drought in PNG as a case study.*

- *develop an effective, dynamic drought 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 development of the drought risk assessment is intended to aid the PNG NWS in informing local PNG stakeholders on which provinces are of highest concern and guide resilient drought risk management practices within priority communities.

Table 1. An analysis of previous drought assessment studies in PNG outlining the methodological aspects lacking.

Study source	Study Description	Effective Methodological Aspects Lacking
Korada et al. 2018	Performed in the Western Highlands province of PNG, which is a rain-fed subsistence farming dominated province highly vulnerable to drought, Korada et al. 2018 adopted GIS and remote sensing technology to highlight potential drought risk zones. General environmental indicators were used to inform the risk assessment: soil type, NDVI, rainfall, terrain, population demography and surface temperature. Using multi-criteria evaluation techniques in GIS, indicators were integrated, and risk areas were identified. Risk areas were mapped and then classified to indicate levels of drought risk from low, medium, and high.	Indicator selection is not specific and tailored; Risk assessment is static; Insufficient validation of indicators and results; Lacks the provision of recommendations for risk reduction; Lacks clear drought risk definitions.
Chua et al. 2020	Used remotely sensed indicators to assess drought over PNG. The indicators evaluated for this study included precipitation, vegetation health and soil moisture. Indicators were assessed on a monthly timescale from 2001 to 2018. A case study was then performed to determine the efficiency of such indicators to characterise drought in PNG during the 2015-2016 El Niño. This case study was used as a validation for indicator effectiveness in assessing drought impacts in PNG. It was found that Vegetation Health Index (VHI) and the Standardized Precipitation Index (SPI) were able to accurately indicate the spatial and temporal components of the 2015 to 2016 severe drought event in PNG caused by the El Niño phase. Overall, these satellite-derived precipitation products were recommended as potentially useful for operational use for drought detection and monitoring in PNG.	Inconsistent drought risk definitions: This is a hazard-centric assessment of drought impacts across PNG; The role of ecosystems and ecosystem services as a driver of risk is not explored.
Allen & Bourke 1997	An assessment of the risk of drought impacts was undertaken in response to the severe 1997-1998 El Nino induced drought in PNG. The impacts of the drought specifically on food supplies and water, on the national scale, were examined. Assessment teams, consisting of experts, were sent out to report on food supply conditions in rural communities, identify placed in severe need, assess migration out of impacted areas, assess local drinking water supply, assess health conditions, and report on the existence of emergency services and communications. Local people were interviewed and observed to obtain the information. Assessment teams each focused on specific area, provinces, or regions. The assessment was conducted over four weeks.	Inconsistent drought risk definitions: although vulnerability, exposure and hazard aspects of drought risk were considered in this study, no clear definitions were provided for drought risk; Lacks the provision of recommendations for risk reduction; No drought risk mapping was conducted; Risk assessment is static; Insufficient validation of indicators and results; Indicator selection is not specific and tailored: although a specific focus on food and water supply was employed, the assessment asked general questions about food and water supply and did not use specific indicators relevant to PNG.

Bang et al. 2003	Agricultural drought risk in PNG was assessed in response to the 2002 drought in PNG, using software developed by the Queensland Centre for Climate Applications. This software used correlations with the Southern Oscillation Index (SOI) and the Pacific Sea Surface Temperature (SST) to assess droughts. Overall drought risk in this study was classified as very low, low, moderate, high, and very high. Indicators considered for the agricultural drought assessment included: population density, slope of agricultural land, drought tolerance of crops, staple crop prevalence, altitude, reliance on agriculture, diversity of cropping systems, and use of irrigation systems, land use intensity, rainfall variability, precipitation deficiency and soil water deficiency. The assessment was carried out through surveys of local farming families residing in severely affected highland and lowland regions across PNG. The results of the study allowed for the following recommendation: a consistent implementation program of long-term farm-specific coping strategies is required in the vulnerable areas throughout PNG, particularly in the highland provinces.	Inconsistent drought risk definitions: although hazard, vulnerability and exposure indicators are considered, these components are not defined; Indicator selection is not specific and tailored: the selection process is not described in detail, with more focus given to the selection of assessed sites; Insufficient validation of indicators and results: no sensitivity analysis was performed to assess the robustness of indicators; No drought risk mapping was conducted.

The significance of our study in addressing these knowledge gaps is now described in section 4.6 of the discussion:

4.6 Research Significance and Conclusions

This study aimed to expand drought risk knowledge, explore effective methodological aspects of drought risk assessment, and develop a preliminary drought risk assessment methodology intended for use in PNG. Such research is minimal across Pacific SIDS, and particularly underexplored in the context of PNG (Hagenlocher et al. 2019). This study made significant strides in addressing key knowledge gaps commonly missed in drought risk assessment studies in general, and drought assessment in PNG specifically, by considering specific and tailored indicator selection, consistent drought risk definitions, dynamic assessment, sufficient validation of indicators and results, and the provision of recommendations.

In this study, an unprecedented attempt at developing a tailored drought risk assessment for the provincial scale across PNG was made. The development of a tailored, meaning highly specific to the area under investigation, drought risk assessment methodology has been recognised as vital to improving risk knowledge for the development of resilient drought risk management strategies in vulnerable communities (Wilhelmi and Wilhite 2002). Out of the disaster risk assessments that have been conducted in PNG, they have used arbitrary risk indicators (Bang et al., 2003; Allen & Bourke, 1997; Korada et al., 2018) and have been conducted on a broader (national/regional) level rather than local area (provinces) or community level (Hagenlocher et al. 2019). This research presents a methodology emphasising tailored risk assessment, with distinct criteria used to select suitable drought risk indicators. 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 and include local user consultation in the indicator selection process, however this is beyond the scope of the current research because of travel/resource limitations, and the remoteness of local PNG communities.

This study adopted the drought risk definitions consistent with those recommended by Hagenlocher et al. (2019). No such study has been conducted previously in PNG, where clearly defined hazard, vulnerability and exposure components are included to assess risk for all provinces. The assessment was intended to be dynamic, but limitations saw that it was only semi-dynamic. Due to data restrictions, the vulnerability and exposure components of the risk assessment consisted of annually updated, static indicators. Whereas the hazard component included dynamic factors. Thus, the approach is deemed a semi-dynamic drought risk assessment. For the assessment to become wholly dynamic, socio-economic data needs to become more readily available. The constrained availability of relevant, reliable, and updated data is recognised as majorly detrimental to drought risk assessments across the world (González Tánago et al. 2016). The semi-dynamic assessment can still provide important results, static assessment is useful for identifying where the origins and drivers of drought risk exist, and the areas that are of priority for long-term adaptation plans (Blauhut 2020, Hagenlocher et al., 2019 and González Tánago et al. 2016).

Indicators used and results produced underwent preliminary validation; however, a more comprehensive validation method is recommended for future research. The risk assessment methodology developed in this research was overall deemed valid. It provides the foundation for conducting drought risk assessments in PNG, to increase risk knowledge and inform local drought risk management. To consolidate this methodology as *reliable in an operational sense, results must undergo validation against further ground-truth sources (e.g local accounts of past drought events). Results allowed for recommendation on disaster risk reduction in PNG, including the identification of priority areas that were detrimentally affected in previous drought, as well as recommendations for improved efficacy of the risk assessment methodology. This is a critical step commonly omitted from the risk assessment process ((Blauhut 2020, Hagenlocher et al., 2019 and González Tánago et al. 2016).*

Overall, this research establishes an essential foundation for tailored and accurate drought risk assessments in Pacific SIDS, using drought in PNG as a case study. However, improvements to the validation methods and the indicator selection process are vital to the efficiency of the risk assessment methodology. Once refinements are made, the risk assessment methodology may be adopted on a more operational basis in PNG. The PNG NWS could conduct drought risk assessment across PNG to inform stakeholders and local users of provincial risk levels, and guide preparedness plans/risk management (Pulwarty and Sivakumar 2014). Such a methodology has the potential to not only be applied across PNG but could be tested for implementation in other vulnerable Pacific SIDS (Finucane 2009). With the occurrence of droughts expected to be exacerbated under anthropogenic climate change, and the impacts 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 effective implementation of valid drought risk assessment is needed now more than ever (Pulwarty and Sivakumar 2014).

The discussion is partly lacking teeth, especially a critical evaluation of your own methods. I'm missing a general discussion on your methods for the following:

• approach of selecting data

• selected/applied data

• data manipulation (averages, spatial and temporal averages? sums?)

• data standardisation practise

• weighting schemes

• risk combination method

• the inclusion of impact information in a statistical manner (risk assessment)

The following sections have been added in the discussion to address this comment, with effort taken to evaluate the methods used in the study:

4.4 Reasonability of Validation Methods

The validation method adopted in this study used literature sources discussing past drought events in PNG as the ground-truth for what occurred during previous droughts. A more reliable ground-truth would have been the perspectives of local PNG people who personally experienced the drought conditions and ensuing impacts (Fragaszy et al. 2020). 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. González Tánago et al. (2016) recommend the use of multiple ground-truth sources, to strengthen validation methodology. Bijaber (2018) adhered to this recommendation and used historical on-the-ground data as well as expert knowledge of what occurred, to validate the results of their drought risk monitoring in Morocco. Due to the data scarcity in PNG, and the additional limitation of not being present in the country to conduct this research, the assessment here could only include one kind of ground-truth source. Future research should consider interviewing local communities in each PNG province to add another, more robust ground-truth for the impacts of each drought event investigated.

Using statistical sensitivity analysis as a second form of validation is recommended as best practice for validating drought risk assessment methodology (Hangelocher et al., 2019). Rahmati et al. (2020) conducted a sensitivity analysis to validate the use of specific indicators for assessing drought risk in south-eastern Queensland. The sensitivity analysis outlined which indicators were highly suitable for use in the risk assessment, highlighting that plant-available water capacity, the percentage of soil comprised of sand, and *mean annual precipitation were the most important predictors of drought for the study (Rahmati et al. 2020). Such best practice was adhered to in this study, with the use of sensitivity analysis as a second form of risk assessment verification. Overall, the use of both a comparison to a ground-truth source, and a sensitivity analysis, for validation of this study is a reasonable approach.*

4.5 Study limitations and recommendations for further research

4.5.1 Indicator Selection Process

In the literature, it is indicated that current practice for indicator selection is to select indicators based on a review of literature (Frischen et al., 2020) and use of current expert knowledge (Dayal et al., 2018). Indicators are commonly arbitrarily selected for the country they are to be used to assess. It is common for data restrictions to be a limiting factor of indicator selection (Dayal et al., 2018). As this study seeks to select specifically suitable indicators for assessment of drought risk on a more localised scale in PNG, to achieve a tailored drought risk assessment, it would have been ideal to select indicators not only based on a literature review or current expert knowledge, but also established with local knowledge 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.

4.5.2 Static Indicators

Vulnerability and exposure indicators were static, using annually updated observed data, due to limited data availability. Although regularly updated data is not available for the vulnerability and exposure indicators, a holistic drought risk index still requires these two components in addition to the hazard component. The hazard indicators used were dynamic, incorporating regularly updated monitoring data. 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. However, this risk assessment is not intended to predict drought events before they happen, it is intended to be used to determine the risk of a drought event occurring and the relative impact that might be faced by specific PNG provinces during a drought. Overall, the semi-dynamic nature of this assessment is not likely a limitation that will reduce the value of this preliminary risk assessment methodology.

4.5.3 Data Availability

Limited data availability constrained several aspects of the methodological process:

- *The validation method was constrained by the fact that there were limited numbers of scientifically robust literature sources reporting on the 2019 drought event, as it was a recent event. The PNG National Weather Service was consulted to ensure that the results from the 2019 literature sources were true and accurate.*

- *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) are not as accurate as VHI; VHI has been proven to be efficient and accurate, specifically for across PNG (Chua et al., 2020).*

Data availability was also limited for the exposure and vulnerability indicators, thus, the data available closest to the time investigated was used. This meant that the vulnerability and exposure indices were the same for both 2014 and 2015 as the data was not updated throughout those two years. However, as half the indicators in both *the vulnerability and exposure are more static rather than dynamic (excluding agricultural occupation, key crop replacement cost, population density and access to safe drinking water), it is not expected that values would largely change on a yearly basis regardless, rather it would be more likely for values to change every two or three years (Aitkenhead et al., 2021). Therefore, the limited data availability for vulnerability and exposure indicators in 2014-2015 will not likely have a large effect on the credibility of the results. Data availability is constrained throughout many SIDS like PNG; future investment in open-sourced and cloud-based data platforms would allow for collaboration between separate entities that have collected data so that all relevant data can be combined, stored, and accessed from the same place (Sun et al., 2020).*

When working in such countries as Pacific SIDS and other developing nations, data availability is commonly scarce (Chua et al., 2020). Several previous studies have come across this limitation and have addressed it in similar ways. In their drought risk assessment in China, Zhao et al. (2020) faced data limitations for the more local level. They chose to use provincial data where county level data was missing. As in this study, Frischen et al. (2020) were faced with limited data availability for drought vulnerability indicators, so it was decided that static indicators would be used rather than temporally-dynamic indicators. Although not dynamic, Frischen et al. (2020) deemed that there was merit in their drought vulnerability assessment, as results offered to expand the underexplored topic of drought risk in Zimbabwe.

- *This research presents a preliminary validation of a tailored risk assessment methodology which is conceptually applicable to the local level. With tailored explicitly meaning that indicators were selected based on rigorous criteria outlining suitability to this study's context. 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.*

4.5.4 Weighting scheme

Although used in many similar past studies, like Frischen et al. (2020), the expert weighting scheme approach has been described by some as unreliable for the delivery of robust results, due to the presence of subjective judgements (Dayal et al., 2018). Furthermore, the sensitivity analysis results suggest that the weighting scheme applied to indicators may not have been optimal. In the future, a revised set of indicator weights should be employed, based off the sensitivity analysis results. As this study was a preliminary assessment, initially attempting to address drought risk assessment knowledge gaps in PNG, the limitations of the weighting scheme do not take away the value of results. So, it was determined that improvements were not required at this stage of the research but are set to be made in future work. Before the drought risk assessment methodology can be adopted for operational use and/or applied to additional Pacific SIDS, weighting refinements will be completed.

Beyond the content, I please you to shorten the method section where possible and double check for repetitions in results, discussion, and conclusions.

The paper overall has been significantly shortened, within the bounds of keeping the critical information. As per your instruction, effort has been made to eliminate repetition from the paper, particularly in the methods, results, discussion/conclusion sections.

Anonymous referee #2

The main issue is the calibration of the risk assessment. For such an analysis to be used operationally, as is the main objective mentioned by the authors, it must clearly distinguish between low and high-risk situations. At present, the analysis shows at least mild risk levels, even in periods when droughts are not observed. The authors also mention that this methodology could be applied to multi-hazard systems. Let us Imagine a situation room where civil protection must prioritise its activities during a non-drought period or even during a flood event where simultaneously the drought risk maps show at least a medium level of risk. What kind of decision making can be derived from such a system?

The intentions of the assessment, and its proposed use has now been clarified further in the introduction, and the discussion sections.

- At the end of the introduction the following sentence has been added:

The development of the drought risk assessment is intended to aid the PNG NWS in informing local PNG stakeholders on which provinces are of highest concern and guide resilient drought risk management practices within priority communities.

- Additionally, this comment has been addressed in the discussion, with realistic instructions added for how such an assessment could be used and what recommendations/decisions could likely be made off such an assessment. Furthermore, we have added more explanation as to why mild risk levels are still observed even in periods of non-drought, and how this does not take away from the value of the risk assessment:

4.2 PNG non-drought years

2014, 2017, 2018 and 2020 were deemed to be non-drought years due to the comparison of risk assessment results and literature analysis results. Even though 2014 and 2020 displayed high enough drought risk levels across PNG's regions to signal that a drought event may have occurred in these years, there was insufficient evidence in the literature to corroborate this. Only a small number of sources reported these years as drought years (Allan et al., 2019; Burivalova et al., 2017; Mckenna and Yakam, 2021; Bhardwaj et al., 2021b). The risk assessment may have identified high risk levels throughout these years as they lead up to (in the case of 2014) or followed (in the case of 2020) confirmed drought. Further investigation on these years is recommended to confirm the validity of the risk assessment. 2017 displayed mostly mild risk throughout all PNG regions, as corroborated in the literature, signalling an end to the 2015-2016 drought event.

Although 2018 was indicated as a non-drought year with most provinces displaying mild or moderate risk, there were some provinces with severe or extreme risk. These higher levels were particularly present throughout the Southern Region. This is not an entirely 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 higher levels, it is not radical to suggest that the final drought risk index would be higher than mild for most years. It is important to note that in this study, it is recognised that drought risk does not directly translate to the occurrence of a drought, rather it corresponds with the severity of impacts likely to be experienced by the area of investigation when a drought occurs. For example, mild drought risk levels seen in certain provinces on the drought risk maps in this study do not necessarily mean that a mild drought is occurring, instead it suggests that mild drought impacts are likely to occur in those provinces. Such mild impacts could occur because of a drought event or could occur because of the regular dry season of PNG (Bhardwaj et al., 2021b). Comparatively, moderate to extreme risk levels are most likely the result of a drought event (Kanua et al., 2016).

In non-drought years, where hazard is low but vulnerability and/or exposure remain 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 (Pulwarty and Sivakumar 2014). Management actions that could be taken in non-drought years to foster resilience in PNG include strengthening of health services, cultivating/planting drought resilient crops, and increasing water storages in highly vulnerable and exposed areas (Hagenlocher et al., 2019). The importance of risk assessment-informed resilient management is highlighted further in the monthly case study of the extreme drought year of 2015.

- It is agreed that the usefulness of our assessment was overstated in the previous version of this paper, at the end of the discussion we make it clear the realistic usefulness of such an assessment:

Overall, this research establishes an essential foundation for tailored and accurate drought risk assessments in Pacific SIDS, using drought in PNG as a case study. However, improvements to the validation methods and the indicator selection process are vital to the efficiency of the risk assessment methodology. Once refinements are made, the risk assessment methodology may be adopted on a more operational basis in PNG. The PNG NWS could conduct drought risk assessment across PNG to inform stakeholders and local users of provincial risk levels, and guide preparedness plans/risk management (Pulwarty and Sivakumar 2014). Such a methodology has the potential to not only be applied across PNG but could be tested for implementation in other vulnerable Pacific SIDS (Finucane 2009).

In the revised manuscript the authors make explicit the difference between a static and dynamic assessment. However, it seems that both approaches are still mixed. I agree that the root causes of risk do not disappear during non-drought events, however, that is what "static" risk analyses are useful for, where the root causes, drivers and drought-prone regions are identified. For instance, such kind of maps are useful for determining long-term adaptation measures.

Further clarification on the nature of the risk assessment is provided. It is now deemed as a semi-dynamic assessment.

The following information on this has been added to the methods section 2.2 to address this:

The assessment is deemed as semi-dynamic as it has a dynamic hazard component, that can be updated monthly, and includes monitoring indicators with data on 3-month cumulative timescales, but also includes more static components of vulnerability and exposure, which are updated annually.

Information is also added in the discussion to further address this and clarify the semi-dynamic nature of our assessment:

4.5.2 Static Indicators

Vulnerability and exposure indicators were static, using annually updated observed data, due to limited data availability. Although regularly updated data is not available for the vulnerability and exposure indicators, a holistic drought risk index still requires these two components in addition to the hazard component. The hazard indicators used were dynamic, incorporating regularly updated monitoring data. 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. However, this risk assessment is not intended to predict drought events before they happen, it is intended to be used to determine the risk of a drought event occurring and the relative impact that might be faced by specific PNG provinces during a drought. Overall, the semi-dynamic nature of this assessment is not likely a limitation that will reduce the value of this preliminary risk assessment methodology.

Clarification was further added in the final section of the discussion:

The assessment was intended to be dynamic, but limitations saw that it was only semi-dynamic. Due to data restrictions, the vulnerability and exposure components of the risk assessment consisted of annually updated, static indicators. Whereas the hazard component included dynamic factors. Thus, the approach is deemed a semi-dynamic drought risk assessment.

As presented here (e.g., section 4.4: "Warnings that are framed in the context of risk would be provided on various timescales (mainly weekly and monthly updates), depending on user needs"), the present analysis should be useful for interventions during or right after an event occur, where the maps would help to prioritise assistance to the most affected areas. In this context, during non-dry periods the warning level should be null. Otherwise, this information is useless. A good example of a dynamic drought risk assessment can be found in the RDrI indicator in the Global Drought Observatory. This also affects validation, as having constant warning levels from medium to high will certainly allow drought events to be detected at the expense of having a high false alarm rate the rest of the time. In an EWS context, surely no one will trust this information. If the authors want to somehow consider the drivers and root causes of risk, please consider another type of analysis as the users are likely to be very different from those using an EWS.

All EWS information has been taken out of the paper, as its relevance and direct link to the purpose of the paper is admittedly unclear. Therefore, claims regarding warnings informed by the risk assessment have been deleted. This addresses this comment.

Moreover, the approach followed for the sensitivity analysis is a bit unclear. As explained in the manuscript the metric used evaluates the range between each indicator only for one year (2015), then somehow "the indicator data value in question was instructed to change in 0.1 increments (spanning from 0.1 to 1)." Not clear how the entire assessment was performed or how this contributes to the uncertainty in the calculations of the overall risk or how the SI could inform the weighting scheme remains unclear.

This need to be clarified. Please, elaborate more on this section as well as the results. E.g., why only 2015 was selected for sensitivity analysis?

The performance of the sensitivity analysis, as well as its usefulness has been elaborate upon in the methods section as well as the discussion section.

In the methods, the following has been added to section 2.2.4 Methodology: Part 4:

Sensitivity analysis provides insight into how uncertainty in a model's output (in this case the hazard, vulnerability, or exposure index) can be attributed to different sources of uncertainty in the model input (in this case the individual indicators) (González Tánago et al. 2016). A sensitivity analysis was conducted for the risk assessment to determine how sensitive the indices were to changes in indicator values. The analysis results were used to identify priority needs for revising the weighting of indicators, to ensure that the most robust indicators are given the most merit in index calculations. 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. It was deemed that this year would be representative of how the risk assessment would perform in a drought event.

The sensitivity analysis performed was a one-way analysis. As such, one input parameter (indicator) used in the calculation of an output (hazard, vulnerability, or exposure index) was varied individually to assess the impact that it would enact upon the output. For example, the sensitivity of the hazard index to changes in SPI was analysed separately to the sensitivity of the hazard index to changes in VHI. Data tables were created in Microsoft Excel for each indicator in each index. In the individual data tables, 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, 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. An example data table is included in Appendix A. The output values were then used to calculate the Sensitivity Index (SI), indicating the sensitivity of the index in question to the individual indicator in question, following Equation 10 (adapted from Farok and Homayouni (2018)).

$$SI = (Dmax - Dmin)/ Dmax \qquad (10)$$

where Dmax is the output result (hazard, vulnerability, or exposure value) when the indicator value in question is set at its maximum value and Dmin is the result for the minimum indicator value. A high SI means high sensitivity, vice versa, with 'sensitivity' meaning the magnitude of the index reaction to changes in indicator data.

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. Provincial SI's were averaged to determine an overall SI for each indicator. The higher the indicator SI is, the more sensitive the relative index 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. 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, based on the sensitivity results (first being the most credible for inclusion in the index) (Anand e t al., 2019).

Appendix A was also added to support this information:

6.1 Appendix A
An example of the data tables used in the sensitivity analysis. This example is for Bougainville province, analysing the sensitivity of the 2015 hazard index to 0.1 incremental changes in the SPI value. Note: original data tables were formatted in excel, and therefore appear differently to the example provided here.

Bougainville	
SPI	Hazard Index
Original	0.561564
0.1	0.339167
0.2	0.389167
0.3	0.439167
0.4	0.489167
0.5	0.539167

0.6	0.589167
0.7	0.639167
0.8	0.689167
0.9	0.739167
1.0	0.789167

In the discussion, the following has been added to section 4.4:

Sensitivity analyses are neglected in the few drought assessments performed for PNG. Without sensitivity analysis, the indicators used in past PNG drought assessment studies cannot be definitively concluded as credible. For example, SPI and VHI were investigated by Chua et al., (2020) for assessing drought in PNG, but were only validated through a 2015-2016 case study of drought impacts. No sensitivity analysis was performed. Like Chua et al., (2020), SPI and VHI are considered in this study. A sensitivity analysis can confirm the credibility of these indicators for use in assessing drought across PNG.

In this study, it was found that no single indicator displayed a seriously high SI value, so each indicator selected for use in the risk assessment is likely credible. This suggests that the hazard, exposure, and vulnerability indices calculated in this study are robust and able of representing the complex processes that lead to drought risk (Anand e t al., 2019). However, based on the different SI values expressed and differences in likely credibility of individual indicators, a review of the weighting applied to each indicator may be appropriate.

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. Previous drought risk assessment studies, conducted in other countries, that have employed SPI and VHI as hazard indicators, commonly weight SPI highly in the hazard index calculations, and VHI usually has a mid-range weighting (Nagarajan and Ganapuram, 2015). Here, a similar approach is taken, however in PNG specifically, it may be pertinent to weight VHI slightly higher (as indicated by the sensitivity analysis).

Generally, global drought risk assessment studies adopt a range of vulnerability indicators that focus on agricultural, economic, and/or health-related vulnerability. In an assessment including economic, health and agricultural vulnerability indicators to detect drought vulnerability in Zimbabwe, Frischen et al. (2020) used an expert weighting scheme to assign indicator weights. Agricultural indicators were commonly assigned the highest weighting, with economic indicators weighted second, and health indicators weighted third (Frischen et al. 2020). Here, the expert weighting scheme followed this trend, with staple crop tolerance score and key crop replacement cost weighted the highest, agricultural occupation weighted third and, children weighed at clinics less than 80% weight for age 0 to 4 years old weighted the least. The sensitive analysis results reveal that a revision is needed. The vulnerability index was evidently most sensitive to changes in the staple crop tolerance score indicator; it is likely incorrect that it is weighted highest. 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. 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. The weighting of agricultural occupation is likely valid as it was found to be the second lowest indicator in terms of credibility.

In many past risk assessments, access to safe drinking water and population density are weighted highly among exposure indicators (Nagarajan and Ganapuram, 2015; Dayal et al., 2018). Whereas land use is generally weighted with mid-range values and slope weighted with lower values (Dayal et al., 2018). The sensitivity analysis results of this study suggest that such weightings should be revised in the case of assessing drought exposure in PNG. Results show land use to be ranked last among exposure indicators in terms of credibility. Currently, land use is weighted the greatest among exposure indicators. This suggests that the weighting assigned to land use should be reduced. Elevation type, population density and access to safe drinking water were found to 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.

Whilst refinements to the weightings applied to hazard, vulnerability and exposure indicators are recommended in the future, they would be minimal as the differences in SI values between indicators within each index were not immense. Overall, the sensitivity analysis results do not retract from the value of the risk assessment results produced in this preliminary study.

On the manuscript structure, the paper was already long, now with the new additions in the revised version it has become even longer and, in some sections, repetitive. The authors still should make an effort to focus and synthesise it, which will surely give it a greater impact.

The paper overall has been significantly shortened, within the bounds of keeping the critical information. As per your instruction, effort has been made to eliminate repetition from the paper, particularly in the methods, results, discussion/conclusion sections.

It is mentioned several times that the methodology is novel (e.g. abstract, line 22. etc), however these methods are not new, certainly could be the first time is used in PNG (which is fair enough), but this does not make the method novel. Please be clear and do not oversell the novelty of this manuscript.

This is true. Effort has been made to display the research significance of the research, whilst recognising that the methodology is not entirely novel. Information has been added to demonstrate how our research addresses methodological knowledge gaps in drought risk assessment studies, particularly in the context of PNG.

The following information has been added at the end of the introduction:

1.5 Addressing drought risk assessment knowledge gaps in PNG

Generally, drought is insufficiently investigated on the global scale (Blauhut, 2020). Out of the few drought risk assessments previously conducted, most are lacking in effective methodological components (González Tánago et al. 2016). Blauhut (2020) recommends that future studies must "improve the characterisation of drought risks and its components" and "ascertain how this risk can be communicated…to enhance resilience to drought". Hagenlocher et al. (2019) corroborates that there are major gaps in previous risk assessment methodologies, like a lack of tailored indicator selection.

Tailored drought risk assessment is specific for measuring drought risk in a particular area and produces information for a certain set of stakeholders. This can be achieved by selecting hazard, vulnerability and exposure indices that specifically consider the climatic, socio-economic, and geographic characteristics of the area being assessed. Thus, generalised indicators would be omitted from the assessment. In recognising the importance of tailoring drought risk assessment through appropriate selection of indicators, Le et al. (2021) selected specific indicators for their agricultural drought risk assessment in Vietnam, based on three criteria (i) indicators are relevant to agricultural sector; (ii) data for these indicators are quantitative and publicly available, and (iii) indicators are specific to Vietnam's socio-economic conditions.

The scarce number of previous studies in PNG, assessing the risk of negative drought impacts, are commonly lacking in effective methodological aspects, and do not address key knowledge gaps in drought risk assessment investigation. An analysis of previous drought assessment studies in PNG is provided in table 1, and the methodological knowledge gaps are outlined. Overall, there is room for future investigation to develop a drought risk assessment to be utilised in PNG that incorporates the most effective methodological aspects, specifically considering the following: tailored and specific indicator selection; consistent drought risk definitions; dynamic rather than static assessment; sufficient validation of indicators and results; and the provision of recommendations for risk reduction.

Accordingly, this study will expand on previous research (Bhardwaj 2021b; Kuleshov 2020) with an aim to increase drought risk knowledge in PNG. Specifically, this research seeks to:

- *demonstrate the potential for tailored drought risk assessments to accurately inform on drought risk levels before, during and after a drought event and thus contribute to more resilient drought risk management in local areas, using drought in PNG as a case study.*
- *develop an effective, dynamic drought 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 development of the drought risk assessment is intended to aid the PNG NWS in informing local PNG stakeholders on which provinces are of highest concern and guide resilient drought risk management practices within priority communities.

The following information has been added at the end of the discussion/conclusion section:

4.6 Research Significance and Conclusions

This study aimed to expand drought risk knowledge, explore effective methodological aspects of drought risk assessment, and develop a preliminary drought risk assessment methodology intended for use in PNG. Such research is minimal across Pacific SIDS, and particularly underexplored in the context of PNG (Hagenlocher et al. 2019). This study made significant strides in addressing key knowledge gaps commonly missed in drought risk assessment studies in general, and drought assessment in PNG specifically, by considering specific and tailored indicator selection, consistent drought risk definitions, dynamic assessment, sufficient validation of indicators and results, and the provision of recommendations.

In this study, an unprecedented attempt at developing a tailored drought risk assessment for the provincial scale across PNG was made. The development of a tailored, meaning highly specific to the area under investigation, drought risk assessment methodology has been recognised as vital to improving risk knowledge for the development of resilient drought risk management strategies in vulnerable communities (Wilhelmi and Wilhite 2002). Out of the disaster risk assessments that have been conducted in PNG, they have used arbitrary risk indicators (Bang et al., 2003; Allen & Bourke, 1997; Korada et al., 2018) and have been conducted on a broader (national/regional) level rather than local area (provinces) or community level (Hagenlocher et al. 2019). This research presents a methodology emphasising tailored risk assessment, with distinct criteria used to select suitable drought risk indicators. 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 and include local user consultation in the indicator selection process, however this is beyond the scope of the current research because of travel/resource limitations, and the remoteness of local PNG communities.

This study adopted the drought risk definitions consistent with those recommended by Hagenlocher et al. (2019). No such study has been conducted previously in PNG, where clearly defined hazard, vulnerability and exposure components are included to assess risk for all provinces. The assessment was intended to be dynamic, but limitations saw that it was only semi-dynamic. Due to data restrictions, the vulnerability and exposure components of the risk assessment consisted of annually updated, static indicators. Whereas the hazard component included dynamic factors. Thus, the approach is deemed a semi-dynamic drought risk assessment. For the assessment to become wholly dynamic, socio-economic data needs to become more readily available. The constrained availability of relevant, reliable, and updated data is recognised as majorly detrimental to drought risk assessments across the world (González Tánago et al. 2016). The semi-dynamic assessment can still provide important results, static assessment is useful for identifying where the origins and drivers of drought risk exist, and the areas that are of priority for long-term adaptation plans (Blauhut 2020, Hagenlocher et al., 2019 and González Tánago et al. 2016).

Indicators used and results produced underwent preliminary validation; however, a more comprehensive validation method is recommended for future research. The risk assessment methodology developed in this research was overall deemed valid. It provides the foundation for conducting drought risk assessments in PNG, to increase risk knowledge and inform local drought risk management. To consolidate this methodology as reliable in an operational sense, results must undergo validation against further ground-truth sources (e.g local accounts of past drought events). Results allowed for recommendation on disaster risk reduction in PNG, including the identification of priority areas that were detrimentally affected in previous drought, as well as recommendations for improved efficacy of the risk assessment methodology. This is a critical step commonly omitted from the risk assessment process ((Blauhut 2020, Hagenlocher et al., 2019 and González Tánago et al. 2016).

Overall, this research establishes an essential foundation for tailored and accurate drought risk assessments in Pacific SIDS, using drought in PNG as a case study. However, improvements to the validation methods and the indicator selection process are vital to the efficiency of the risk assessment methodology. Once refinements are *made, the risk assessment methodology may be adopted on a more operational basis in PNG. The PNG NWS could conduct drought risk assessment across PNG to inform stakeholders and local users of provincial risk levels, and guide preparedness plans/risk management (Pulwarty and Sivakumar 2014). Such a methodology has the potential to not only be applied across PNG but could be tested for implementation in other vulnerable Pacific SIDS (Finucane 2009). With the occurrence of droughts expected to be exacerbated under anthropogenic climate change, and the impacts 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 effective implementation of valid drought risk assessment is needed now more than ever (Pulwarty and Sivakumar 2014).*

Equations 1,2, 3 the indicators are mentioned as standardised, please elaborate on how these were standardised and please explain how this connect with the absolute thresholds mentioned in table 2.

Elaboration has now been provided on the standardisation process. Information has been added to section 2.2.2 Methodology: Part 2:

To calculate the hazard, vulnerability, and exposure indices, indicator data was first reclassified by a linear function (using the rescale by function tool in ArcGIS Pro) 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 (Equation 1).

$$\mu A(x): X \longrightarrow [0,1] \qquad (1)$$

where μA(x) refers to the grade of membership for element x in a fuzzy set A, and the X is the universal set.

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 and fuzzy large . 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.

In fuzzy large, larger inputs have membership values closer to 1. This function is defined by a midpoint value that can be left as a default or manually adjusted to suit specific datasets, which is assigned a membership of 0.5. Equation 2 gives the mathematical expression for fuzzy large membership.

$$\mu(x)= 1/(1+ 〚(x/f2)〛^{(-f1)}) \qquad (2)$$

where f1 is the spread and f2 is the assigned midpoint.

In fuzzy small, smaller inputs have membership values closer to 1. Like fuzzy large, it is defined by a either a default or manually assigned midpoint that is given a membership value of 0.5. Equation 3 gives the mathematical expression for fuzzy small membership.

$$\mu(x)= 1/(1+ 〚(x/f2)〛^{f1}) \qquad (3)$$

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.

Clarity has also been provided for the fact that the thresholds presented in table 2 (now table 3) are not included in any of the calculation processes.

The following information has been added to 2.2.1 Methodology: Part 1:

Each of the selected hazard, vulnerability and exposure indicators have varying thresholds for signalling levels of drought risk. Table 3 provides the generally accepted thresholds for each indicator in which 'no to mild drought risk, 'moderate drought risk', and 'severe to extreme drought risk' is likely signalled. These thresholds have been determined through an investigation of literature regarding each indicator. For example, SPI and

VHI thresholds were decided upon using guidance from Chua et al., (2020). These thresholds are provided as an insight into the general signals given by ranges of values in the indicator data. They were not used further in any calculations.

Part 3. The methodology shows all years fall under some level of risk; it is not clear how the literature review confirms that the two events mentioned are represented. What about the other years showing different levels of risk? 470-475. This is a qualitative assessment, not sure why the authors limited only to 8 reports where for the 2015 more reports are available. Which records were selected? According to which criteria?

Further clarification on the literature review process has now been added to the methods. Information has been added as to why the number of sources were selected, how records were selected and what criteria was used for selection. Additionally, detailed information of what impacts were described in the literature to constitute the identification of a drought event is now included. Please note: the literature investigation was conducted for all years throughout 2014-2020, and a certain set of search parameters were used. Thus, there was potential for description of risk levels in non-drought years. However, no sources that were selected for use in the literature investigation described drought risk conditions in non-drought years.

The following information was added to 2.2.3 Methodology: Part 3:

A literature search was undertaken to gather appropriate sources for analysis. Criteria for the inclusion and exclusion of sources was developed, guided by similar past studies (González Tánago et al. 2016) and the requirements of this study. Table 6 displays the criteria used to select sources for this study. The search parameters used to gather the sources are listed in Table 7. Overall a total of 13 sources (Annamalai et al. 2015; Whitfield et al., 2019; Bonnafous et al., 2017; Government of Australia, 2017; Allan et al., 2019; De Deckker, 2016; Schmidt et al., 2021; Burivalova et al., 2017; Bhardwaj et al., 2021b; Johnson et al., 2019; Bang and Crimp, 2019; World Food Programme, 2019; Mckenna and Yakam, 2021) were included in the literature investigation (Table 8). Each of the 13 sources were analysed and the following information was recorded: the time of drought mentioned, the severity of drought mentioned, and the types of drought impacts mentioned. The specific provinces mentioned, and the severity of impacts described for such provinces, were also recorded.

Table 6. Inclusion and exclusion criteria for the selection of literature sources to be used in the risk assessment validation.

Criteria for inclusion	Criteria for exclusion
Literature in English	Literature in other languages
Mention of a specific time period in Papua New Guinea within which drought was present and/or drought impacts were experienced.	Vague mention of drought events overall in the history of Papua New Guinea, with specific years not mentioned and/or mention of drought in years prior to the study period.
Impacts of drought are mentioned in a detailed manner, with the specific type of impacts described. Mention of specific impacts in particular PNG provinces.	Drought conditions are briefly mentioned, with no reference to specific drought impacts experienced in PNG, or in specific provinces.
Drought impacts described are not only meteorological/hazard impacts, socio-economic/vulnerability/exposure impacts are also mentioned.	Only meteorological/hazard impacts are described (e.g temperature anomalies)
Publicly available government/relevant organisation documents, Open access Journal articles, review articles and book chapters	Restricted access books/book chapters, journal/ review articles, and grey literature other than relevant organisation documents (meteorological organisation documents), for example newspaper articles

Table 7. Search parameters used to gather literature sources for the risk assessment validation.

Database	Search Parameters	Result
Google Scholar	1st search: "Papua New Guinea" AND "drought impacts" Filtered date from 2014-2020 (study period)	1st search: 101 items found, 7 Included, 94 Excluded

	2nd search: "Papua New Guinea" AND "drought impacts" AND "La Nina" AND "El Nino" Filtered date from 2020-2021	2nd search: 16 items found, 2 Included, 10 Excluded, 4 Repeated
ScienceDirect	1st search: Drought AND Papua New Guinea Filtered date from 2014-2020 (study period) 2nd search: Papua New Guinea AND drought impacts AND La Nina AND El Nino Filtered date from 2020-2021	1st search: 502 items found, 0 Included, 500, Excluded, 2 Repeated 2nd search: 2 items found, 0 included, 2 excluded, 0 repeated
Springer Link	1st search: Drought event AND Papua New Guinea AND impacts Filtered date from 2014-2020 (study period) 2nd search: Papua New Guinea AND drought impacts AND La Nina AND El Nino Filtered date from 2020-2021	1st search: 48 items found, 2 Included, 45 Excluded, 1 Repeated 2nd search: 3 items found, 0 included, 2 excluded, 1 Repeated
Wiley Online Library	1st search: Drought AND Papua New Guinea AND impact AND province Filtered date from 2014-2020 (study period) 2nd search: Drought AND Papua New Guinea AND impact AND province Filtered date from 2020-2021	1st search: 134 items found, 3 Included, 129 Excluded, 2 Repeated 2nd search: 27 items found, 0 included, 14 excluded, 13 repeated

Table 8. Literature sources used as a ground-truth. The source is listed and described with the types of impacts listed in the sources recorded.

Source	Drought Period Mentioned	Severity of Drought Mentioned	Types of Impacts Described for PNG
Annamalai et al. 2015	2015-2016	Severe to extreme	-Famine -Compromised freshwater supplies and food security -Impacts on public health, economies, and food distribution
Whitfield et al., 2019	2015-2016	Severe to extreme	-Climatological effect, which varied with elevation. -Extreme high temperatures were recorded at lower elevations, coinciding with bush fires and severe drought impacts -At mid-elevation, there were reductions in dry season rainfall and the increases in temperature were less severe, due to the mediation of cloud effects -intermittent frosts occurred at particularly high elevations. -impacted crops both directly through drought and frost, and indirectly, through changes in ecosystem services and disservices, including pest pressure and predation of pests.
Bonnafous et al., 2017	2015-2016	Severe to extreme	-the Ok Tedi mine experienced several months of shutdown after a drought induced by the 2015 El Niño event.
Government of Australia, 2017	2015-2016	Severe to extreme	-reduced rainfall in many areas of PNG from April 2015 -reduced cloud cover in high altitude locations in July-August led to damaging frosts. -the rural population experienced reduced access to clean drinking water and staple foods, which resulted in health problems. -there was an increase in mortality
Allan et al., 2019	2014-2016	Severe to extreme	-the drought event had very severe societal, agricultural, environmental, and ecological impacts -severe drought and associated food shortages impacted Papua New Guinea
De Deckker, 2016	2015	Severe to extreme	-El Niño conditions in mid-2015 led to almost a third of the PNG population experiencing famine due to crop failure
Schmidt et al., 2021	2015-2016	Severe to extreme	-the severe 2015-2016 El Niño event decimated a critical share of PNG's local crop production, leaving 10 per cent of the population with significant food shortages.
Burivalova et al., 2017	2014-2015	Severe to extreme	-the 2014–2015 El Niño event, which caused unusual precipitation patterns in Papua New Guinea, had severe drought impacts

Bhardwaj et al., 2021b	2015-2016 and 2019-2020	Severe to extreme for 2015-2016 Mild for 2019-2021	-there was a strong El Niño-induced drought event in 2015 -there was a weaker La Niña-induced dry period in 2020 -the 2015-2016 event led to devastating negative rainfall anomalies, particularly in the southern mainland -the weak dry event in 2019-2020 was evidently detected over the entire country of PNG, with the first provinces to experience dry conditions being New Ireland, East and West New Britain, Bougainville, and Manus in the north-east of the nation. Impacts experienced in such provinces were likely mild.
Johnson et al., 2019	2019	Mild	-mild drought impacts were detected in PNG during a weak 2019 drought episode
Bang and Crimp, 2019	2015-2016	Severe to extreme	-widespread hunger -malnutrition and in some cases even death due to starvation. -recovery crops like sweet potato were crushed by unseasonal frosts.
World Food Programme, 2019	2019	Moderate	-below average vegetation across most of the country -Western and Gulf Province experienced moderate to severe dry conditions and subsequent impacts. -prolonged drought conditions and moderate drought impacts were recorded in southeast areas of the country. -soil moisture was impacted in the coastal areas and southern part of the country, affecting water storage, irrigation and raising the risk of bushfire.
Mckenna and Yakam, 2021	2019-2020	Moderate	-negative impacts were experienced by market sellers

498. The use of two-tailed p values does not depend on the sample size but on null hypothesis to be tested. Please, motivate better this affirmation.

This has been addressed in 2.2.3 Methodology: Part 3:

The main factor being tested for was if a difference existed between the risk assessment-given risk levels and the literature-given risk levels. As this is non-specific, a two-tailed p-value is deemed appropriate for use (Peskun, 2020).

The authors mention that the weighting scheme should be revised in the future. This is a key point, why it is not assessed here?

The weighting scheme is discussed further in the discussion, with information added to clarify what is meant by our recommendation to revise the weighting scheme in the future.

The potential adjustments to the weighting scheme is discussed in section 4.4 Sensitivity analysis:

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. Previous drought risk assessment studies, conducted in other countries, that have employed SPI and VHI as hazard indicators, commonly weight SPI highly in the hazard index calculations, and VHI usually has a mid-range weighting (Nagarajan and Ganapuram, 2015). Here, a similar approach is taken, however in PNG specifically, it may be pertinent to weight VHI slightly higher (as indicated by the sensitivity analysis).

Generally, global drought risk assessment studies adopt a range of vulnerability indicators that focus on agricultural, economic, and/or health-related vulnerability. In an assessment including economic, health and agricultural vulnerability indicators to detect drought vulnerability in Zimbabwe, Frischen et al. (2020) used an expert weighting scheme to assign indicator weights. Agricultural indicators were commonly assigned the highest weighting, with economic indicators weighted second, and health indicators weighted third (Frischen et al. 2020). Here, the expert weighting scheme followed this trend, with staple crop tolerance score and key crop replacement cost weighted the highest, agricultural occupation weighted third and, children weighed at clinics less than 80% weight for age 0 to 4 years old weighted the least. The sensitive analysis results reveal that a revision is needed. The vulnerability index was evidently most sensitive to changes in the staple crop tolerance score indicator; it is likely incorrect that it is weighted highest. 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. 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. The weighting of agricultural occupation is likely valid as it was found to be the second lowest indicator in terms of credibility.*

In many past risk assessments, access to safe drinking water and population density are weighted highly among exposure indicators (Nagarajan and Ganapuram, 2015; Dayal et al., 2018). Whereas land use is generally weighted with mid-range values and slope weighted with lower values (Dayal et al., 2018). The sensitivity analysis results of this study suggest that such weightings should be revised in the case of assessing drought exposure in PNG. Results show land use to be ranked last among exposure indicators in terms of credibility. Currently, land use is weighted the greatest among exposure indicators. This suggests that the weighting assigned to land use should be reduced. Elevation type, population density and access to safe drinking water were found to 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.

Whilst refinements to the weightings applied to hazard, vulnerability and exposure indicators are recommended in the future, they would be minimal as the differences in SI values between indicators within each index were not immense. Overall, the sensitivity analysis results do not retract from the value of the risk assessment results produced in this preliminary study.

Further clarification on the weighting scheme, and the improvements that may be made, aswell as why these were not made at this stage of the study is now included in section 4.5.4 Weighting scheme:

Although used in many similar past studies, like Frischen et al. (2020), the expert weighting scheme approach has been described by some as unreliable for the delivery of robust results, due to the presence of subjective judgements (Dayal et al., 2018). Furthermore, the sensitivity analysis results suggest that the weighting scheme applied to indicators may not have been optimal. In the future, a revised set of indicator weights should be employed, based off the sensitivity analysis results. As this study was a preliminary assessment, initially attempting to address drought risk assessment knowledge gaps in PNG, the limitations of the weighting scheme do not take away the value of results. So, it was determined that improvements were not required at this stage of the research but are set to be made in future work. Before the drought risk assessment methodology can be adopted for operational use and/or applied to additional Pacific SIDS, weighting refinements will be completed.

Table 2: in the text is mentioned that the variables where standardised before being introduced in the risk analysis. Not clear how the information on this table enter the risk assessment, is a risk matrix? What happen when one indicator indicates extreme risk and the other mild?

This table was just intended to help define the indicators used in terms of different drought risk levels. This has been clarified in the text, with emphasis given to the fact that the information in this table was not in any way used in the index calculations. This clarification is added at the end of section 2.2.1 Methodology: Part 1:

Each of the selected hazard, vulnerability and exposure indicators have varying thresholds for signalling levels of drought risk. Table 3 provides the generally accepted thresholds for each indicator in which 'no to mild drought risk, 'moderate drought risk', and 'severe to extreme drought risk' is likely signalled. These thresholds have been determined through an investigation of literature regarding each indicator. For example, SPI and VHI thresholds were decided upon using guidance from Chua et al., (2020). These thresholds are provided as an insight into the general signals given by ranges of values in the indicator data. They were not used further in any calculations.

Please note that the table spoken about in this comment was previously referred to as table 2, but in the revised document it is table 3.