A risk assessment for major flooding in Myanmar incorporating hazard, exposure, and vulnerability

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Abstract
Worldwide, floods have major impacts on people, economies, and the environment. In Myanmar, floods are a prominent hazard, with frequent extreme inundation heavily affecting people and their livelihoods. Flood risk assessments for Myanmar on the national scale are scarce, and none examine risk from major flood events, yet these are crucial for planning disaster risk reduction. Here we present the first indicator-based risk assessment for a flood event with a 100-year return period at the township level for Myanmar. Our results show that hazard and exposure of people logically follow the pattern of the rivers, however vulnerability to flooding is widespread across the whole country. Using multiplicative aggregation of exposure and vulnerability, and overlaying quantiles of varying severity of these elements to determine risk, it is evident that risk is concentrated in the Ayeyarwady, Bago, and Rakhine states. By incorporating elements of hazard, exposure, and vulnerability, this assessment also reveals factors that contribute to flood risk, and can be used by decision makers to guide effective disaster risk reduction activities.

Highlights
- High risk townships are concentrated in Ayeyarwady, Bago regions and Rakhine States.
- Vulnerability arises from poverty, poor health care access, and poor road networks.
- Population centers e.g. Yangon and Mandalay cities, have high exposure to flooding.
- Flood risk is driven by exposure in the multiplicative index-based approach.

Key words
Flood risk; vulnerability; Myanmar; IPCC framework; Index-based approach

1. Introduction
As a country highly affected by extreme weather events, understanding risk in Myanmar is extremely important. Floods are the most frequently occurring hazard and have the highest contribution to average annual loss compared to all other hazards for the country (ADPC, 2015). In the last 10 years, three major flood events caused high levels of damage and each resulted in over 100 fatalities (Guha-Sapir 2020). In 2015, a riverine flood resulted in over US$1 billion in damages, affected over 1.6 million people, and caused at least 149 deaths (Guha-Sapir 2020). With climate change, Myanmar is likely to continue to experience river flood events at the scale of the 2015 floods or worse (Hirabayashi et al. 2013).

Riverine flooding occurs when water rises over the top of riverbanks and spills into the surrounding area (Nasiri, Yusof, and Ali 2016). In Myanmar some river flooding occurs almost every year with the monsoon season and communities now rely on these floods for nutrient deposition on their agricultural fields (Taft and Evers 2016). Communities have learnt to cope with and have adapted to these annual floods, harnessing their value (Taft and Evers 2016). However, as demonstrated by the impact of the 2015 flood which was characterized to be of a 20-50 year return period (MMPF, 2017), Myanmar has little capacity to cope with major flood events.

To reduce flood risk decision makers must have a holistic understanding of the underlying factors. The Sendai Framework for Disaster Risk Reduction calls for disaster risk management that takes into account all dimensions of disaster risk, including hazard, exposure, and vulnerability (UN-DESA 2015). With comprehensive risk assessments decision makers are better placed to understand the components that contribute to flood risk and work to reduce its impact.

While flood risk assessments using various techniques such as univariate deterministic modeling, probabilistic modelling and damage functions, and index based approaches are becoming more common globally (e.g. Mondal et al., 2020; Nguyen et al., 2018; Pinos et al., 2020), the state of the art is not well developed in Myanmar. Analysis has mostly focused on flood loss estimation (Zin et al. 2020), 2020), flood hazard mapping (Khaing et al. 2019), flood hazard mitigation (Acierto et al. 2018; Lin, Rutten, and Tian 2018), resilience after flood events (Jones and Ballon 2020), or future vulnerability to flooding under climate change and land use change scenarios at the state level (Mandle et al., 2017; Oo et al., 2018a, 2018b; Sritarapipat & Takeuchi, 2018). One recent paper examined flood risk on a national scale for Myanmar (Phongsapan et al. 2019). This paper modelled hazard based on the frequency of flooding from 1984 – 2015 and incorporated factors of exposure and vulnerability through an index-based risk assessment.

So far there are no risk assessments for major flood events at the national scale. We aim to contribute to the broader literature on flood risk in Myanmar and fill this gap by conducting a national, index-based risk assessment at the township administrative level, for a riverine flood with a 100-year return period. There are two main objectives of the paper. First, this analysis will show the spatial distribution of major river flood risk based on the IPCC framing of risk (IPCC 2014b). Second, it will highlight factors of vulnerability that contribute to risk. Together these can be used for decision making for effective flood risk reduction.

2. Methods and Materials

2.1. Case Study

Myanmar is located in south-east Asia (Figure 1). Its land size is approximately 678,500 km2 and it has an estimated population of 42.5 million people (Oo et al., 2020). The country has a complex multi-level governance system with 330 townships at the lowest level of government (Batcheler et al. 2018). Much of the population in Myanmar live in poverty (MMPF, 2017) and the country was ranked 145 out of 189 in the Human Development Index in 2019 (UNDP 2019). There are four major rivers in Myanmar with populations reliant on each (Taft and Evers 2016). The Ayeyarwady is the largest and the most important used in commerce and daily life (Taft and Evers 2016). Most of the country has a tropical monsoon climate, with river floods commonly occurring between May to October (FAO 2016; Taft and Evers 2016).

Figure 1. Myanmar with labelled states. Townships are the next administrative level down.

2.2. Conceptual framework

This paper built on the general risk framework from the IPCC 5th assessment report, where risk is the potential for adverse consequences and is a function of hazard, exposure, and vulnerability (IPCC 2014a). In this analysis we focused on present day flood risk to people. Exposure was defined as the presence of people within the extent of the hazard (IPCC 2014a) – a 100-year flood event. Vulnerability was defined as the propensity or predisposition of the Myanmar people to be adversely affected and encompassed the components of susceptibility and coping capacity (based on the definition in IPCC, 2014a).

2.3. Workflow

Figure 2 outlines the workflow of the quantitative index-based approach for the township level used in this analysis. All data was freely available allowing for replication and validation of this study.

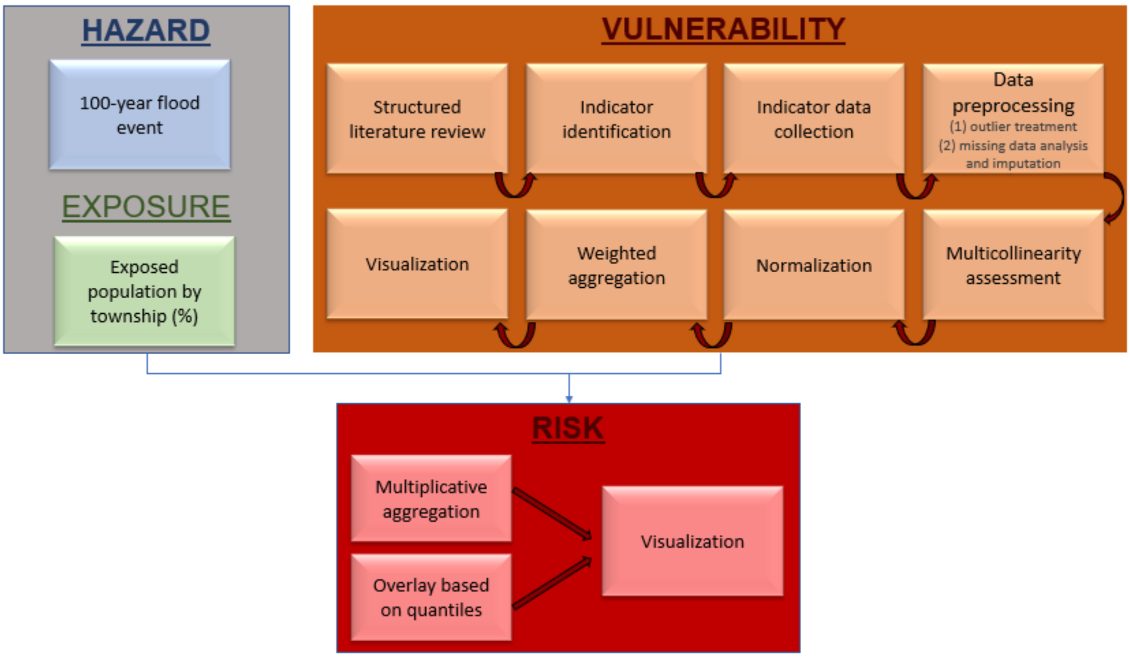


Figure 2. Workflow showing method to determine risk derived from OECD, (2008) *and* Hagenlocher et al., (2018).

2.3.1. Flood hazard/exposure

River flood extent for a 100 year return period was obtained from The Global Risk Data Platform (https://preview.grid.unep.ch/). ArcGIS was used to crop the global dataset to the national boundaries of Myanmar and limit the extent of the flooding to modelled depth above 20 centimetres.

To calculate hazard exposure, we determined the percentage of exposed population per township (e_soc_i) based on the modelled population distribution from WorldPop (WorldPop, 2016) (p_tot_i), and the population within the flood extent (p_exp_i) (Equation 1. i refers to each township).

$$e\_soc_i = \frac{p\_exp_i}{p\_tot_i} \times 100 \tag{1}$$

The percentage of exposed population was normalized using linear min-max (Equation 2) so that the range was reduced to between one (high exposure) and zero (no exposure) to create the exposure index (EI_i). This is a very common normalisation method for indicator based assessments (Beccari 2016).

$$EI_i = \frac{(E_i - E_{min})}{(E_{max} - E_{min})} \tag{2}$$

In Equation 2, E_i refers to the percentage of exposed population before transformation, E_{min} refers to the minimum value of exposure, and E_{max} refers to the maximum value of exposure.

2.3.2. Flood vulnerability

To identify relevant indicators, a systematic literature review was conducted to understand the main drivers and causes of flood vulnerability in Myanmar. Two searches were conducted using Web of Science (WoS) and SCOPUS in May 2020. Search strings were constructed based on the logic in Sebesvari et al. (2016). The authors separately screened all titles and abstracts of the unique papers to determine relevance. Criteria included: focus on Myanmar; risk and vulnerability to flood; and the exposure of people. Publications that met these criteria were selected. Papers that did not were excluded, including those that focused solely on flood hazard. Where one or both authors were uncertain, the paper was read entirely by the authors to determine selection. To find additional grey literature a Google search was conducted. After screening the first 10 pages of results two reports were added to the literature review. At the end of the process, 33 papers were included for final review. A summary of searches is provided in Table 1.

Table 1. Search terms used to capture papers to inform vulnerability indicator identification.

Searches	WoS	SCOPUS	Unique	Included
Search 1: TITLE-ABS-KEY (flood AND (risk OR vulner* OR resil*) AND (eval* OR assess* OR profile OR index OR indic* OR multicriteria) AND (myanmar OR burm*))	25	38	44	11
Search 2: TITLE (myanmar OR burm*) AND TITLE-ABS-KEY (flood)	63	78	96	20
Google search: "Myanmar flood disaster impact"	-	-	-	2

Search strings use SCOPUS operators. For WoS, TOPIC replaced TITLE-ABS-KEY. TITLE remained the same.

Each pertinent study was reviewed to pinpoint elements influencing vulnerability to flooding in Myanmar. These elements were categorized into indicators of susceptibility and coping capacity. Subsequently, township-level data were gathered from various sources, such as the 2014 census and additional surveys. Given the data at hand, 19 indicators were selected for inclusion in the conclusive evaluation (Table 2). Supplementary material I offers a summary of all sought-after indicators identified during the literature review, along with the origins of the data for those utilized.

Table 2. Final list of indicators including code, data source, and direction.

Indicator	Code	Data Source	Direction
Susceptibility			
Dependency ratio (people <15 and >65 years / people between 16-64 years)	s_dep	MIMU 2014	+
Population below the poverty line (average annual income)	s_pov	GAD 2016-17	-
Disability prevalence (population, %)	s_dis	MIMU 2014	+
Population with vector borne diseases (malaria incidence per 10000 people)	s_vec	GAD 2016-17	+
Population with chronic illness (share of tuberculosis, dysentery, and hepatitis, %)	s_chr	GAD 2016-17	+
Female-headed households (%)	s_fhh	MIMU 2014	+
Population affected by conflict in townships in the last year (number of conflict events per 10000 people in the last year)	s_con	ACLED 2020	+
Households with access to safe sanitation (%)	s_san	MIMU 2014	-
Households with access to improved drinking water (%)	s_dri	MIMU 2014	-
Population living in poorly constructed housing (households with walls or floors constructed from leaf, bamboo, or earth, s_wal & s_flo average %)	s_wfl	MIMU 2014	+
Average travel time to the closest city (minutes)	s_ttc	Weiss et al. 2018	+
Daily wage worker (%)	s_daw	GAD 2016-17	+
Coping capacity			
Households with access to information (telephone, mobile, internet, or radio, s_tel, s_mob, s_int, &s_rad max %)	c_ati	MIMU 2014	-
Literacy rate, (%)	c_lit	MIMU 2014	-
Density of roads (road kernel density: km road/km2, search radius = 5km)	c_dens	OSM (2020)	-
Households owning a boat (%)	c_boa	MIMU 2014	-
Number of doctors per 10000 people	c_doc	GAD 2016-17	-
Number of hospital beds per 10000 people	c_bed	GAD 2016-17	-
Households with access to alternative electricity source (households using solar energy or a generator as the main source of lighting, c_sol &c_gen total %)	c_aes	MIMU 2014	-

The indicators concerning access to telephones, the internet, mobile devices, and radios were consolidated into a single information indicator (c_ati), while data on inadequately built floors and walls were combined to form a singular housing conditions indicator (s_wfl). Additionally, information on households possessing generators and solar energy was merged into an indicator for access to alternative electricity (c_aes). Proxy variables were employed for s_pov, s_vec, s_chr, s_con, c_ati, and s_wfl. (for more information, see Supplementary Material I).

In the third phase, outliers were detected and addressed according to the method outlined in (Damioli 2017), utilizing Microsoft Excel. Box plots, leveraging the interquartile range along with skewness and kurtosis measurements, facilitated the identification of extreme values. Given the limited data available for triangulation to ascertain if these extreme values were inaccuracies, the specialized, local knowledge of one of the contributors was applied. It was concluded that only five indicators contained outlier values attributed to errors (s_pov, s_vec, s_chr, s_fhh, and c_doc), which were corrected through winsorization. (see Supplementary Material II).

In the fourth step, the extent of missing data was evaluated. Drawing on insights from Downey & King (1998) and Roth et al. (1999) regarding tolerable limits for missing data, no indicators were omitted since all had missing data below 20%. However, ten townships exhibited missing data exceeding 20% and were thus labeled as highly uncertain in the ultimate risk and vulnerability evaluations. The missing data were compensated for by employing the Inverse Distance Weighting (IDW) tool in ArcGIS and calculating the average from the generated results.

In the fifth stage, an analysis of multicollinearity was performed employing Kendall's Tau and a two-tailed method for determining statistical significance in SPSS (IBM SPSS Statistics), a method frequently applied to data that is not normally distributed (Puth et al. 2015) with r > 0.9 signifying datasets that are highly correlated (Hagenlocher et al. 2018). No concerns regarding collinearity were identified. (Supplementary Material II).

As a sixth measure, the ultimate collection of indicators was normalized to a scale ranging from zero to one utilizing the linear min-max method. For indicators wherein, higher scores indicate greater vulnerability (positive directio n), Equation 3 was utilized. Conversely, for indicators where higher scores reduce vulnerability (negative direction), values were inverted following Equation 4. In Equation 3 and 4, X_i refers to the indicator value for a township (i) before transformation, X_{min} refers to the minimum value of the indicator, X_{max} refers to the maximum value of the indicator, and X_i' refers to the indicator value after transformation.

$$X_i' = \frac{(X_i - X_{min})}{(X_{max} - X_{min})} \tag{3}$$

$$X_i' = \frac{(X_i - X_{max})}{(X_{min} - X_{max})} \tag{4}$$

Lastly, in the absence of specific insights into their relative significance, all indicators were assigned equal weights and combined through additive arithmetic aggregation to formulate the vulnerability index. VI_i (Equation 5).

$$VI_i = \frac{\sum X_i'}{N} \tag{5}$$

In Equation 5, X_i' denotes the normalised indicator values for the township and N refers to the number of indicators.

2.3.3. Flood risk

2.3.3.1. Method one

The vulnerability and exposure indices were combined through the application of two distinct methodologies. First, multiplicative arithmetic aggregation of hazard/exposure (EI_i) and vulnerability (VI_i) was conducted to determine relative risk for each township in a risk index (RI_i) (Equation 6).

$$RI_i = EI_i \times VI_i \tag{6}$$

2.3.3.2. Post hoc analysis of method one

Following the multiplicative combination of indicators, a correlation assessment was carried out to explore the potential link between risk and exposure or risk and vulnerability as a result of the first method. This analysis was performed using Kendall's Tau in SPSS, and scatter plots were generated with Microsoft Excel. Additionally, histograms depicting the distribution of values within the exposure and vulnerability indices were produced in SPSS to offer further understanding.

2.3.3.3. Method two

For the second method to determine risk, we divided the exposure and vulnerability indexes into five quantiles with an equal number of townships. We overlaid different quantiles (Table 3) to show where varying levels of vulnerability and hazard/exposure intersect, to highlight where there were high levels of both.

Table 3. Quantile overlay

Exposure quantile	Vulnerability quantile
5 (very high)	5 (very high)
5 (very high)	4 (high)
4 (high)	4 (high)
4 (high)	3 (medium)
3 (medium)	3 (medium)

3. Results

3.1. Hazard exposure

The analysis showed that the 100-year return period river flood hazard predictably followed the contours of the rivers in Myanmar (Figure 6a). The highly exposed populations and townships also bordered rivers, with most flooding in the Ayeyarwady region followed by the Bago, Mandalay, and Yangon regions (Figure 6b and context map). Populations in 27 townships were not exposed, however in 12 townships, 99 percent or more of the population were exposed to flooding. The capital city Nay Pyi Taw, and the former capital city Yangon, also had a high percent of the population exposed to flooding.

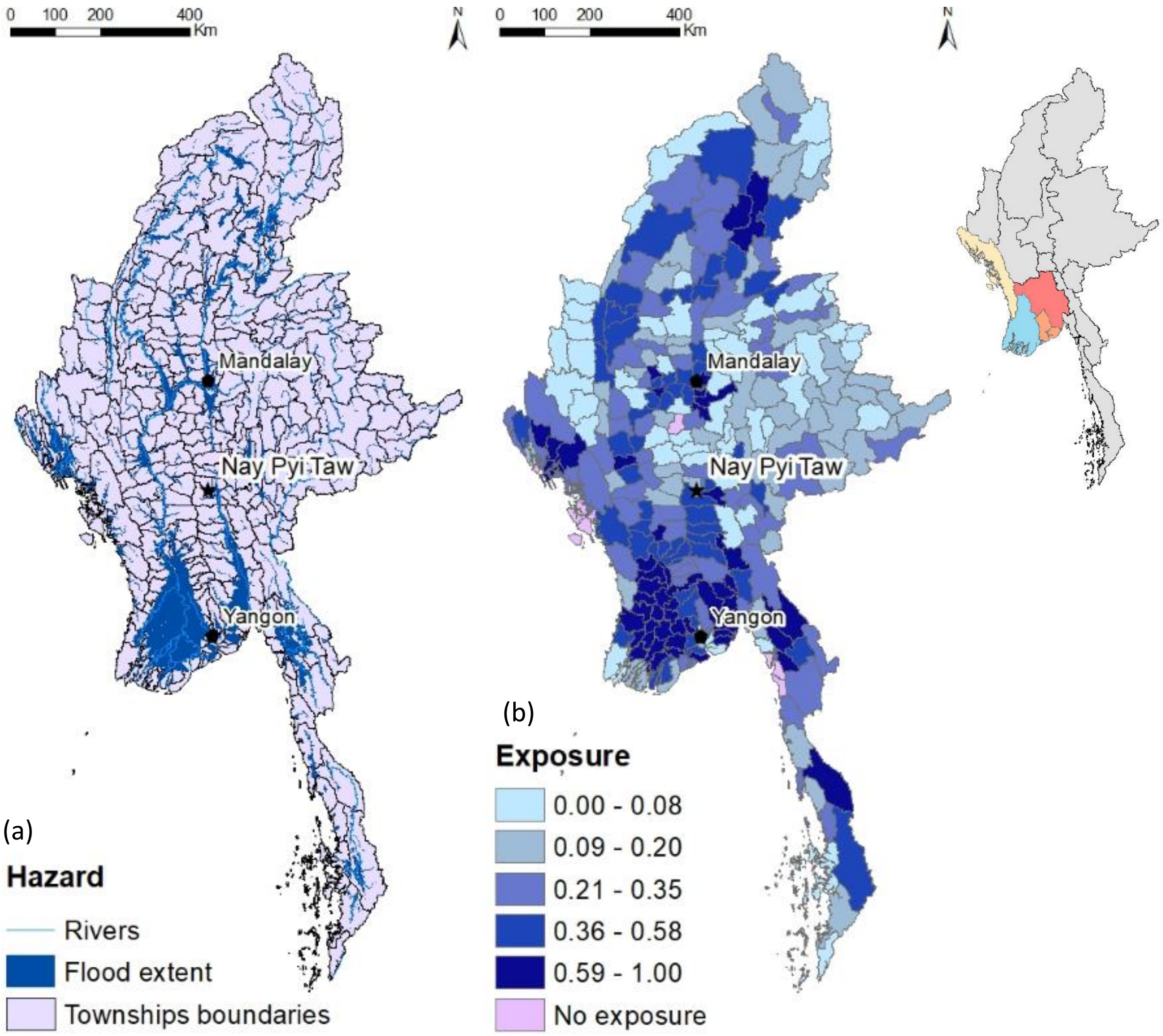


*Figure 3. Results showing (**a**) Spatial analysis of 100-year return period flood hazard and (**b**) exposure to people (classification for exposure: 5 quantiles between 0.001 and 1.0). (Context map insert: yellow=Rakhine, red=Bago, blue=Ayeyarwady & orange=Yangon).*

3.2. Vulnerability

Vulnerability was widespread through Myanmar (Figure 4). Our analysis showed that some vulnerability indicators were more critical than others (Figure 5).

For the five most critical indicators, most townships had an index score between 1.0 and 0.9. Access to healthcare was poor with a maximum of one doctor and 51 hospital beds per 10000 people in 222 and 312 townships, respectively. Accessibility was also low for 290 townships with the density of roads between 0 to 2.82 (road kernel density: km road/km2, search radius = 5km). The percentage of households owning a boat, which are important for saving lives and transportation during flood events, was between zero and 4.86 percent in 242 townships. Poverty was also widespread. The average income for 312 townships was between 324225 to 3720021 Kyat (US$ 251 to US$2884), and 14 townships had an average income below the 2015 poverty line of 475595 Kyat (US$ 369) (MMPF, 2017).

Among the remaining indicators, some contributed to vulnerability more than others. For access to alternative electricity sources such as solar panels and generators that are useful during the power shortages during floods, 199 townships had maximum of 20 percent of households with these facilities. However, conflict, vector borne diseases, and the literacy rate contributed less to vulnerability for most townships.

Spatially, the most vulnerable townships were concentrated in the upper half of Myanmar. The majority of townships in the highest quantile were located in the Shan state, followed by Rakhine and Kachin states. Logically, the least vulnerable townships were concentrated in Yangon region, where the former capital of Myanmar, Yangon, is located. This was followed by the Mandalay region which has the second largest city, Mandalay, and the Nay Pyi Taw Union Territory which is the current capital city.

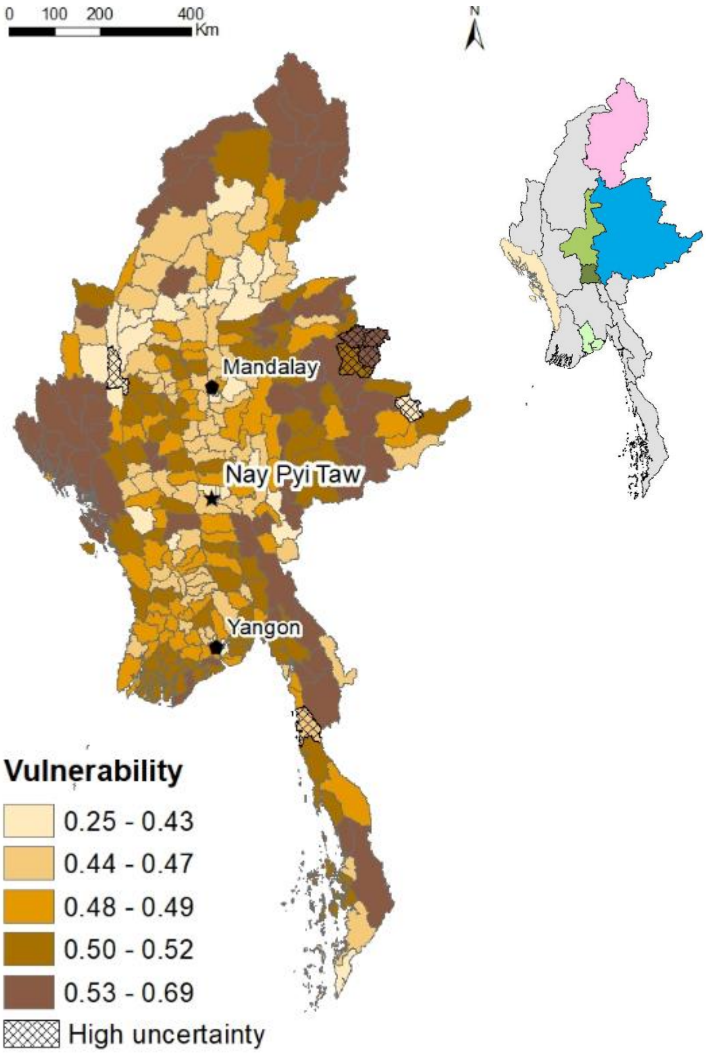


Figure 4. Results showing spatial distribution of flood vulnerability in Myanmar. Classification: 5 quantiles between 0.25 and 0.69. (Context map insert: yellow=Rakhine, dark blue=Shan, pink=Kachin, light green=Yangon, mid green=Mandalay, dark green=Nay Pyi Taw).

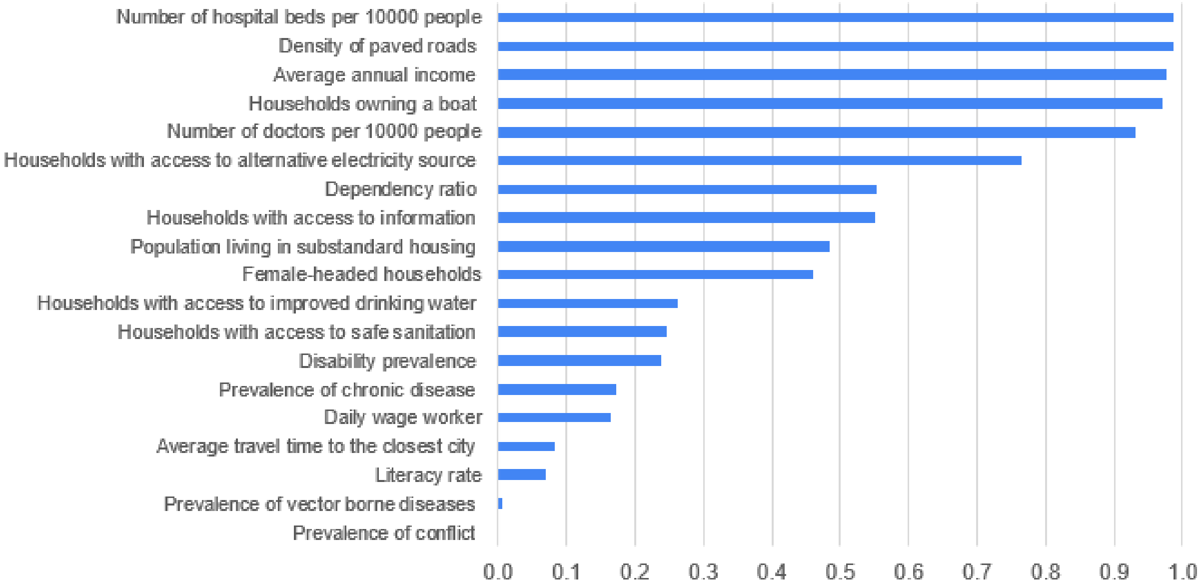


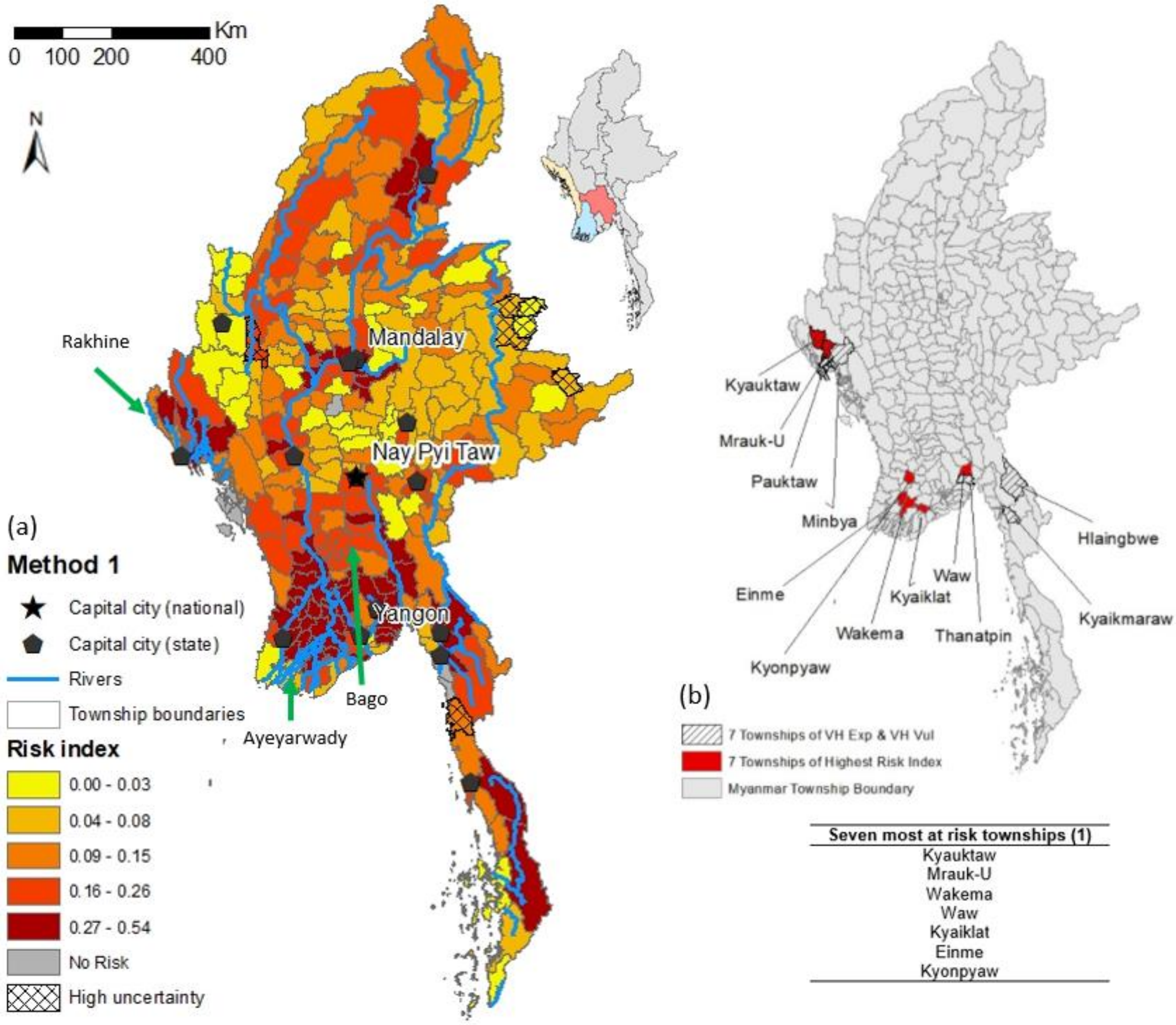
Figure 5. Median scores across townships for all vulnerability indicators.

3.3. Risk

3.3.1. Method one

Figure 6a shows the spatial distribution of risk according to the multiplicative aggregation of vulnerability and exposure. Risk was highly concentrated in townships in the Ayeyarwady, Bago, and Rakhine regions. The seven townships with the highest risk index score are shown in Figure 6b. Due to the absence of exposure to the hazard, there were 27 townships that had zero risk.

The elements contributing to risk for townships in the highest quantile were multi-faceted. Common elements included highly exposed populations between 50-100 percent, high levels of poverty, and a low number of hospital beds and doctors per 10000 people. Both urban and rural areas were present in the highest quantile with the travel time to the nearest city ranging from 0 to 440 minutes. Interestingly, townships with the highest risk experienced no conflict in the last year, and high literacy rates above 95 percent.



Seven most at risk townships (1)
Kyauktaw
Mrauk-U
Wakema
Waw
Kyaiklat
Einme
Kyonpyaw

*Figure 6. Risk results from method one showing (a) Spatial distribution of flood risk at township level in Myanmar (classification: 5 quantiles between 0.001 and 0.54) and (**b**) Map (not to scale) showing the location of the 7 most at risk townships according to method one (red). (Context map insert: blue=Ayeyarwady, light red =Bago, yellow=Rakhine).*

3.3.2. Post hoc analysis

Figure 7 shows that in method one, exposure was strongly significantly correlated to risk (r =.94, p = < 0.001) (a), and weakly correlated to vulnerability although not significantly (r =.06, p = 0.093) (b). When looking at the distribution of vulnerability and exposure index scores, it is clear that exposure was more evenly distributed (c) whereas vulnerability clustered around a mid-point (d).

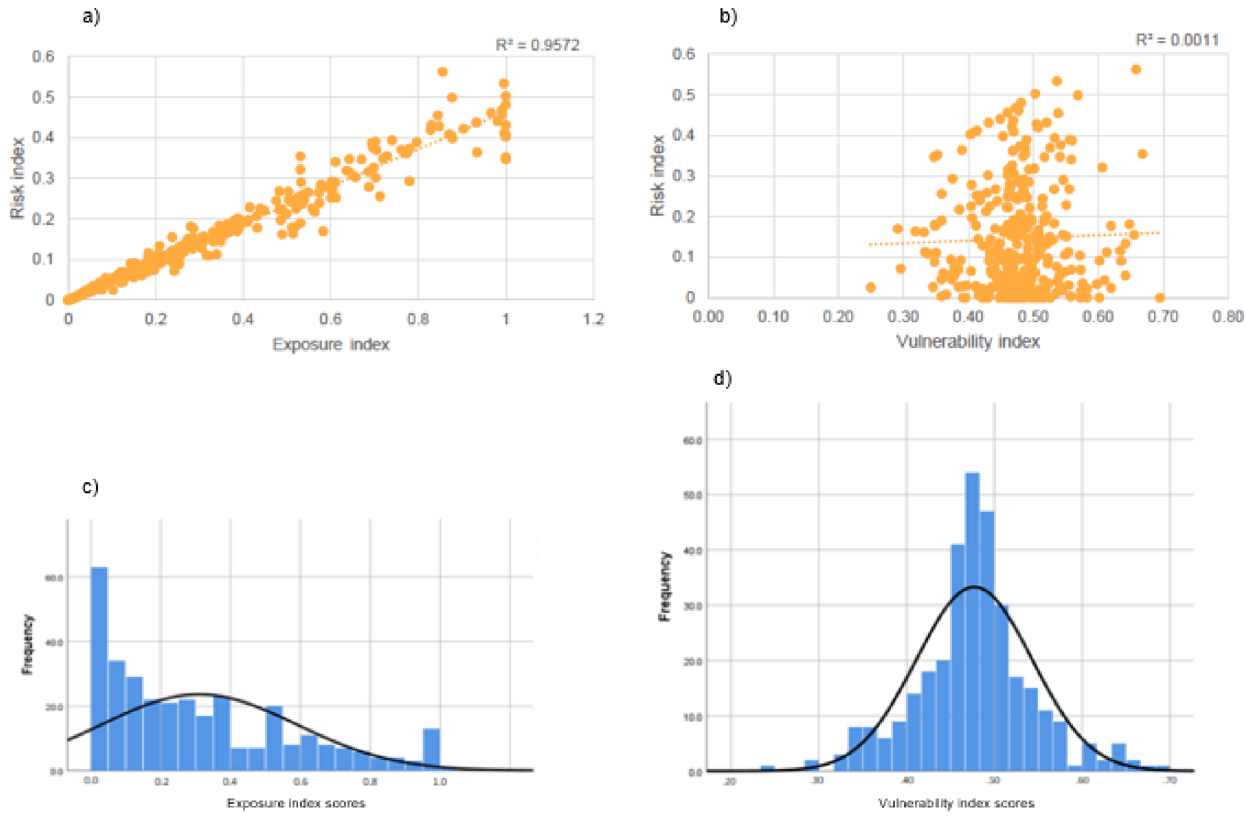


*Figure 7. Results of the post-hoc analysis showing (**a**) exposure is linearly related to risk; (**b**) vulnerability and risk have a weak relationship; (**c**) the distribution of exposure values is broad; (**d**) the distribution of vulnerability values clusters at the mid-point.*

3.3.3. Method two

While risk was driven by exposure in the first method, in the second there was an equal representation of vulnerability and exposure in the risk visualization (Figure 8a). There were 7 townships with very high exposure and vulnerability (Figure 8b) and an additional 10 townships with very high exposure and high vulnerability. Administratively, these 17 townships mostly belonged to the Ayeyarwady, Bago, Yangon regions and Rakhine State. Every state except Kayah and Nay Pyi Taw had at least one township with a minimum of medium vulnerability and exposure (74 townships in total). Common characteristics of these townships were high levels of poverty, poor accessibility with low road density and low access to healthcare with low numbers of doctors and hospital beds per 10000 people. In addition, these townships had relatively high dependency ratios and low access to information.

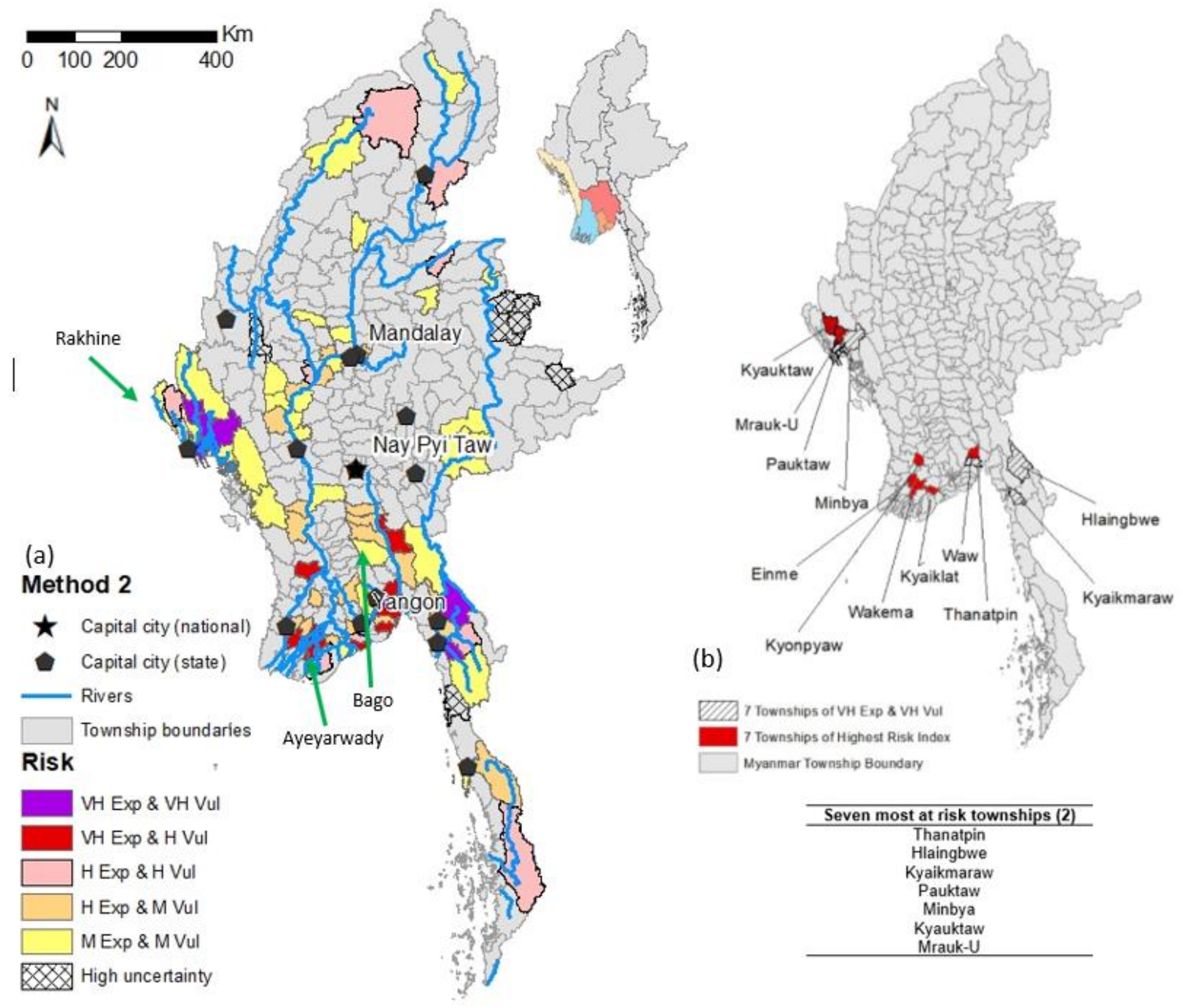


*Figure 8. Risk results from method two showing (**a**) Townships at risk based on the overlay of vulnerability and exposure quantiles and (**b**) Map (not to scale) showing townships with very high exposure and very high vulnerability (lines). (Context map insert: yellow=Rakhine, red=Bago, blue=Ayeyarwady & orange=Yangon).*

4. Discussion

Our study aimed to conduct a conceptually supported risk assessment of river flooding in Myanmar to explore the spatial distribution of risk, and to understand the broad underlying factors of vulnerability that contribute to increased risk to aid decision making. Vulnerability is a fundamental element of risk and an adequate understanding of its dimensions and root causes is vital for constructive risk assessment and risk reduction (Schneiderbauer et al. 2017). A main finding in our analysis is that vulnerability to river flooding in Myanmar is primarily triggered by poverty and inadequate access to public infrastructure and services such as road networks, and health care. Although Myanmar has started the transition to a democracy, the underlying causes of poverty are still rooted in the centralized military rule that lasted for five decades (Hudson-Rodd et al. 2004; The Burma Fund 2003). The consequence of mismanagement of natural resources, state inefficiency, corruption in resource allocation, and social and economic insecurity is continued poverty and vulnerability in Myanmar (Thang, Uyen, and wa Mungai 2014). Moreover, ineffective governance and persistent high levels of poverty have resulted in a growing population living in unsafe areas, with poor infrastructure and housing conditions, contributing to compounding vulnerabilities (GUoM, 2015; World Bank, 2014). Widespread inadequate access to services that assist people in everyday life such as health care and alternative electricity sources has also reduced the potential for economic participation that enables people to escape from poverty, while further limiting capacities to cope and adapt to flooding (Hudson-Rodd et al. 2004). Spatially, the highest vulnerability occurs in ethnically dominated border areas such as Shan, Kachin and Rakhine states where poverty and lack of access to services is especially severe due to the continuing conflicts and violence in the context of counter-insurgency activities (Hudson-Rodd et al. 2004). This has resulted in a situation where it is difficult for people to pursue livelihoods and plan for the future, due to the lack of security (Hudson-Rodd et al. 2004). Social capital is undermined by violence and development agencies and governments have struggled to make an impact as efforts are undermined by destruction of assets and continuing instability (Hudson-Rodd et al. 2004). Foreign investors are reluctant to consider these regions for their business activities further contributing to relative underdevelopment (Hudson-Rodd et al. 2004).

A history of poor governance is also related to river flood exposure in Myanmar. Ongoing deforestation, farmland expansion, and unstructured or poorly planned land use change can be linked back to natural resource mismanagement and state inefficiencies (Bank, 2014; Oo et al., 2020). This has contributed to decreased flood plain areas and high levels of sedimentation and erosion in waterways, worsening flood hazard and increasing exposure of people and assets to floods (Khaing et al., 2021; Taft & Evers, 2016). This is particularly relevant for the Ayeyarwady region which has highest exposure to river flooding due to sedimentation moving through the river systems and settling in the flat deltaic area and the large number of people living and working in the flood plains (Taft and Evers 2016).

Moving beyond a discussion of exposure and vulnerability as separate elements, when comparing the results of the two methods of presenting risk, it is evident that the designation of individual townships as high risk and the relationships between risk, exposure, and vulnerability, can be influenced by the methods used to calculate it. Between our approaches, the townships with highest risk were different, as were the factors contributing to it. In the first approach, there was a strong relationship between risk and exposure, while the range of vulnerability indicator scores for the townships in the highest risk quantile were more widely spread. This was due to the additive aggregation of the vulnerability indicators that resulted in compensability (OECD 2008) and a high proportion of townships with similar vulnerability scores. Conversely, exposure had a much broader range. Thus, when using multiplicative aggregation to calculate risk, exposure had a much greater influence. In the second method, the contribution of vulnerability and exposure was equally shared. For the most critical vulnerability indicators such poverty, road density and healthcare, the vulnerability indicator scores for high risk townships were concentrated at the higher end of the scale. Thus, due to the methodological variations and resulting drivers of risk, the determination of risk for each township was a different for each approach.

However, looking at the spatial distribution of risk on the wider scale and the relative proportion of high-risk townships between states and regions, townships with high risk were concentrated in the Ayeyarwady, Bago and Rakhine states in both approaches. This can be explained by the high levels of vulnerability and exposure in each of these regions. The Ayeyarwady region is a delta region where populations are highly exposed to river flooding due to living and working on the flood plain (Taft and Evers 2016). The large proportion of people pursuing low paid agricultural or fishing livelihoods and the general lack of infrastructure in the region contributes to its vulnerability (Soe 2020; Thein et al. 2019). Bago State is also highly exposed as it is mostly low-lying, lacks downstream discharge capacity, and a major population center, Bago City, is located on one of the rivers' natural levees (Komori et al. 2020). Here, people also pursue agricultural livelihoods and there has been little development of services or infrastructure (Shrestha and Htut 2016). In Rakhine State, populations are highly exposed to river flooding due the extreme rainfall from storms coming directly from the Bay of Bengal (Sarsycki and Towashiraporn 2020). Ongoing conflict and violence in the state has resulted in a highly vulnerable population as well (Hudson-Rodd et al. 2004).

Either representation of risk can be used by authorities depending on their needs. As our conceptual framework specifies that risk results from the interaction of exposure and vulnerability, the second method may be more conceptually supported, pointing clearly to factors of vulnerability that contribute to townships at high risk, while incorporating exposure as well. This method can also be adjusted to show different overlapping levels of exposure and vulnerability to meet the requirements of the user. As they are presented here, both results can help determine which townships to prioritize resources for flood risk reduction by governmental and international humanitarian organizations. Our research also provides information on which vulnerability factors to focus for planning of flood risk reduction strategies. For example, according to our results flood risk reduction programs should consider reducing poverty and improving accessibility, health care, and access to alternative electricity sources.

To validate our study, there is only one of other paper that considers flood risk on a national scale for Myanmar and incorporating exposure and vulnerability, by Phongsapan et al. (2019) (although a different framework and definitions were used). Both analyses showed that exposure is very high in Ayeyarwady and Yangon and that Shan state is the most vulnerable region. High risk regions that presented in all results were the Ayeyarwady Delta and Rakhine state. Areas of difference were in the far north and south of the country, where both our risk analysis showed areas with medium to high risk, however Phongsapan's analysis showed low risk. Future work on flood risk assessment validation in Myanmar would be useful. Validation using loss and damage data may be difficult due to the paucity of data on the scale required, however workshops with local risk experts could provide an alternative method.

While comprehensive, there are several significant limitations in this study and future work could focus on addressing these gaps. Conceptually, this study focuses on the risk of flooding to people, however in Myanmar many impacts of flooding arise from damages and losses to crops and croplands (GUoM, 2015; Taft & Evers, 2016; UN OCHA, 2015). To better comprehend flood risk and have a holistic understanding of drivers or methods for risk reduction, a social-ecological risk assessment is necessary. In addition, river floods do not occur in isolation to other hazards. This study considered river flooding, however coastal and pluvial floods are also common and can result in compound events (Taft and Evers 2016). Similarly, flooding has triggered other hazards such as landslides, resulting in greater impact (GUoM, 2015). This analysis provides insight into risk from river flooding, however consideration of multi-hazards would better determine risk levels (Marzocchi et al. 2012), and help inform programs or policy that targets risk from multiple hazards, improving outcomes for the people in Myanmar. A final conceptual limitation is that flood extent is only one characteristic of hazard that contributes to damage. Flood depth, duration, and velocity also contribute to the impact of floods (Lin et al. 2018; Liu, Siu, and Mitchell 2016). Consideration of these conceptual challenges in future risk assessments could improve the results.

In addition to conceptual limitations, there are several data and knowledge-based limitations that should be considered when using this assessment, and addressed in the future. Firstly, the threshold of flood damage starting at 20 centimeters was arbitrary and more localized research is needed to understand at what height floods start to cause damage. Secondly, additive aggregation to create the vulnerability index resulted in the compensability of indicators. The extent to which indicators are compensable is unknown, and in some cases unlikely, for example high literacy rates offsetting low numbers of boats. Thirdly, equal weighting of indicators was used in the vulnerability analysis however, some indicators would be more important than others for flood vulnerability and risk. Fourthly, the accuracy of the population distribution from WorldPop was unclear as some townships had hundreds of thousands more, or less, people than were counted in the 2014 census without transparent justification. Lastly, indicator data were from different sources, collected in different years, some imputation was required, and data for every vulnerability indicator was not available, especially for coping capacity. The issues with data analysis explored here are common in index-based assessments (Fekete, 2012), and introduce uncertainty into the accuracy of the results. A sensitivity analysis such as analyzing the effects of missing indicators or alternative aggregation methods, and further validation analysis would help confirm our findings.

Nevertheless, the results of our study are essential for local and national authorities and funding organizations as it is the first risk assessment with strong conceptual foundation of risk for Myanmar, incorporating a clear vulnerability perspective. It could be used to inform disaster risk reduction programs or develop risk transfer mechanisms for high risk hotspots. Our findings also stress the need for institutional reforms regarding corruption and effective governance due to their links with factors increasing vulnerability and flood risk. To better target flood risk reduction policies and programs at the township or community level, it is recommended to conduct further research to understand localized underlying causes of flooding hazard, exposure, and vulnerability in high risk areas, and increase the resilience of those communities.

5. Conclusion

This paper presents the first, conceptually sound risk assessment for major flooding in Myanmar showing risk at the township level. The findings highlight the value of incorporating the elements of hazard, exposure, and vulnerability to reveal the regions at high risk, and the factors driving critical levels of vulnerability that contribute to risk. This assessment also suggests the influence of underlying causes on present day vulnerability. The results of this assessment can be built upon, either through methodological or conceptual improvements, or by looking in more detail and at a finer resolution at the identified areas of high risk. Policies and programs can target the high-risk regions and critical factors of vulnerability identified in this assessment for effective disaster risk reduction in Myanmar as well.

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Supplementary material I
Indicators

Table A provides details of all the relevant indicators for flooding in Myanmar. Indicators that were not included due to lack of data are highlighted red. Direction refers to the impact of the indicator on vulnerability and risk. A positive (+) sign indicates that a higher score increases vulnerability and risk. A negative (-) sign indicates that a higher score decreases vulnerability and risk.

Table A. List of desired indicators with references, data sources (where applicable), and justification.

Social Exposure							
Category	**Indicator**	**Code**	**Direction**	**References**	**Data Source**	**Justification**	**Comments**
Exposure	Percentage of the population exposed to river floods (%)	s_exp	+	(IPCC 2014a)	Hazard: UNEP Preview Population: WorldPop 2020 (modelled)	Without population exposure to a hazard there is no risk to the population.	Hazard return period: 100-years
Social susceptibility							
Category	**Indicator**	**Code**	**Direction**	**References**	**Data Source**	**Justification**	**Comments**
Poverty and inequality	Dependency ratio (%)	s_dep	+	(GUoM), 2015; A. T. Oo et al., 2018b; Phongsapan et al., 2019)	Census 2014	Both young and elderly individuals often rely financially on the state or their families. They might require help during evacuations and are at a higher risk of contracting illnesses, including waterborne diseases.	This demographic dependency is quantified by adding the populations under 15 years and over 65 years, then dividing by the population aged 16-64 years.
	Average annual income	s_pov	+	(GUoM), 2015; Win et al., 2018)	General Administration Department Survey 2016-17	A low average income indicates that the township may lack access to goods, services, and opportunities, possessing minimal reserves to withstand economic shocks. Consequently, these areas will face challenges in rebounding after a flood event.	Proxy for: Population below the poverty line (%)
	Households with existing debt (%)	s_deb	+	(GUoM), 2015; A. T. Oo et al., 2018a)	-	Existing debt limits the capacity to obtain additional credit following a flood, indicating financial strain within the community.	
	Minority population (%)	s_min	+	(Burki 2015)	-	Minorities often encounter challenges in accessing education, employment, and credit due to structural inequalities.	
Disability and health status	Proportion of population with a disability (%)	s_dis	+	(GUoM), 2015)	Census 2014	A high prevalence of individuals with disabilities places additional demands on communities owing to increased dependency, resulting in a greater need for assistance during floods.	Disability defined by MIMU (2018) as seeing, hearing, walking, remembering.
	Number of cases of malaria per 10,000 people	s_vec	+	(Burki 2015; Oo et al. 2018a, 2018c; Phongsapan et al. 2019)	General Administration Department Survey 2016-17	Vector-borne diseases amplify the health burden on communities. Floods expand breeding sites for disease vectors, further escalating the risk of contracting these illnesses.	Proxy for: Population with a vector borne disease (%)
	Percent share of the incidence of tuberculosis, dysentery, and hepatitis (%)	s_chr	+	(Oo et al. 2018a)	General Administration Department Survey 2016-17	Chronic diseases impair individuals' capacity to engage in activities that build capital and heighten the necessity for aid and specialized care during floods.	Proxy for: Population with chronic illness (%)
	Population undernourished (%)	s_nou	+	(GUoM), 2015)	-	Undernourishment adversely affects education, employment, and health outcomes, hindering overall well-being and productivity.	
Gender	Female-headed households (%)	s_fhh	+	(GUoM), 2015; Kawasaki et al., 2020)	Census 2014	Females' limited access to education, employment, land, and credit detrimentally influences the entire household's well-being and economic stability.	

Stability/ conflict	Number of conflict events per 10000 people in the last year	s_con	+	(GUoM), 2015)	Conflict: The Armed Conflict Location & Event Data Project Population: WorldPop	Conflict is highly pertinent to Myanmar, impacting individuals' capacity to attain livelihood objectives and ongoing instability severely hampers development initiatives.	Proxy for: Population affected by conflict in townships (%) Time: June 1, 2019-June 1, 2020. Includes: battles, explosions, riots, and violence against civilians.
	Proportion of internally displaced persons (%)	s_idp	+	(GUoM), 2015)	-	This population lacks a safety net, faces limited shelter options, and experiences emotional trauma.	
WASH	Households with safe sanitation (%)	s_san	-	(Boutry, 2017; GUoM), 2015)	Vulnerability assessment 2018 based on Census 2014	Poor sanitation contributes to adverse health outcomes. Unsealed sanitation facilities can contaminate waterways during floods, exacerbating health risks further.	Defined by MIMU (2018) as flush and improved pit latrine.
	Households access to improved drinking water supply (%)	s_dri	-	(Burki, 2015; GUoM), 2015; Htein et al., 2018; A. T. Oo et al., 2018a, 2018c)	Vulnerability assessment 2018 based on Census 2014	A poor drinking water source is associated with negative health outcomes. During and following a flood, water from non-improved sources is at a higher risk of contamination, further heightening health hazards.	Defined by MIMU (2018) as tap, tube well, protected well, and bottled water.
Settlement and Housing	Households with walls or floors made from leaf, bamboo or earth (%)	s_wfl	+	(GUoM), 2015; Kawasaki et al., 2017, 2020; Otsuyama et al., 2019; Win et al., 2018; Zin et al., 2020)	Census 2014	These houses are prone to damage or complete destruction during a flood, resulting in a diminished availability of quality shelter for affected populations.	Proxy for: The population residing in poorly constructed housing. Calculated by averaging the percentage of houses with walls made from materials such as leaf, bamboo, or earth, and the percentage of houses with floors constructed from similar materials.
	Population living in informal settlements (%)	s_ins	+	(Boutry 2017)	-	These individuals are less likely to be prioritized by aid agencies and governmental bodies, leading to limited access to essential services.	
	Population living in unofficial wards (%)	s_unw	+	(Boutry 2017)	-	These individuals are less likely to be considered by aid agencies and governmental authorities, resulting in restricted access to essential services.	
Remoteness	Average travel time to the nearest city (minutes)	s_ttc	+	(Phongsapan et al. 2019; Sritarapipat and Takeuchi 2018)	The Malaria Atlas Project 2015	This determines the ease of accessing services typically available only in urban areas, such as healthcare, and also signifies access to markets, creditors, and other amenities..	
Employment	Daily wage workers (% of working population)	s_daw	+	(GUoM), 2015; UN OCHA, 2015; Win et al., 2018)	General Administration Department Survey 2016-17	During disruptions, daily wage workers are typically the first to lose employment, leading to a decline in income.	
Coping capacity							
Category	**Indicator**	**Code**	**Direction**	**References**	**Data Source**	**Justification**	**Comments**
Information/ early warning	Households with access to radio, television, internet, or mobile (max %)	c_ati	-	(GUoM), 2015; Htein et al., 2018; A. T. Oo et al., 2018a)	Census 2014	People can receive warnings, access additional information about the flood, and locate services to aid in coping with the situation.	Proxy for: Households with access to information (%)
	Number of rain gauges per 10 000km	c_rai	-	(Yuan et al. 2019)	-	Provides precise data for early warning systems.	
	Presence early warning system (yes/no)	c_ear	-	(Htein et al. 2018; Oo et al. 2018c; Otsuyama et al. 2019; Reeder 2019)	-	Early warning facilitates prompt evacuation.	Potential proxy: Households that received early warning in last event (%)

Social capital	Population that has lived in the township for more than 1 year (%)	c_ltr	-	(Jones and Ballon 2020; Kawasaki et al. 2020; Phongsapan et al. 2019)	-	Indicates familiarity with the area, knowledge of evacuation routes, and social connections that would be beneficial during and following a flood.	
Education	Literacy rate (%)	c_lit	-	(Jones and Ballon 2020; Kawasaki et al. 2020; Phongsapan et al. 2019)	Census 2014	Literate individuals can read informational materials and warning pamphlets, as well as complete forms to access assistance. Literate people have more awareness regarding disaster risk than illiterate people.	
Institutional capacity	Money spent on disaster risk reduction per person.	c_res		(Htein et al. 2018; Oo et al. 2018c; Otsuyama et al. 2019; Reeder 2019; Zaw and Lim 2017)	-	Indicates the institutional capacity to support the population and the existing systems designed to aid communities in coping with challenges.	Potential proxy: Number of disaster risk reduction projects per 10000 people
Transportation	Households owning a boat (%)	c_boa	-	(Kawasaki et al. 2020; Otsuyama et al. 2019; UN OCHA 2015)	Census 2014	Boats are valuable assets during floods for evacuating people and transporting essential goods.	
Health	Number of doctors per 10000 people	c_doc	-	(Boutry, 2017; GUoM), 2015; Htein et al., 2018; A. T. Oo et al., 2018a, 2018c; Phongsapan et al., 2019)	General Administration Department Survey 2016-17	A population requires doctors to address illnesses and injuries following a flood.	This aspect was not aggregated with c_bed since, even if there are enough hospital beds, the absence of doctors renders treatment unavailable.
	Number of hospital beds per 10000 people	c_bed	-	(Boutry, 2017; GUoM), 2015; Htein et al., 2018; A. T. Oo et al., 2018a, 2018c; Phongsapan et al., 2019)	General Administration Department Survey 2016-17	Populations require access to hospital beds to receive essential healthcare services.	This aspect was not aggregated with c_doc since, without hospital beds, it becomes difficult for populations to access doctors and receive necessary treatment.
Access to energy	Households with access to alternative electricity sources (%)	c_aes	-	(Oo et al. 2018a)	Census 2014	After floods, there is a high likelihood of damage to electricity transmission wires. Alternative sources of power can assist communities in remaining safe by providing light, charging devices, and enabling communication with others and authorities.	Solar energy and generators were identified as alternative energy sources. The total number of these sources per township was aggregated and divided by the number of households to calculate the average number of alternative energy sources per household.
Accessibility	Density of roads (road kernel density: km road/km2, search radius = 5km)	c_dens	-	(Boutry, 2017; GUoM), 2015; UN OCHA, 2015)	Open Street Map 2020	The presence of roads enhances accessibility for emergency vehicles and serves as evacuation routes for populations.	Trunk, primary, secondary, and tertiary roads were taken into account. Data was downloaded on 6/6/2020.
Settlement and housing	Houses with more than one floor (%)	c_flo	-	(Zin et al. 2020)	-	Residents can relocate furniture to higher ground to mitigate flood damage, evacuate to safer areas, or reside on higher floors of buildings during flooding.	
Financial capital	Households with diverse incomes (%)	c_div	-	(GUoM), 2015; Kawasaki et al., 2020; A. T. Oo et al., 2018a)	-	if one source of income is disrupted due to flooding, households can rely on alternative sources of income to sustain themselves.	
	Households with savings (%)	c_sav	-	(GUoM), 2015)	-	In the event of income disruption, individuals can depend on savings to cover expenses.	
	Households with insurance (%)	c_ins	-	(GUoM, 2015; Kawasaki et al., 2020)	-	This provides financial security and facilitates the rebuilding process after a flood.	
Public infrastructure	Average distance to nearest shelter place.	c_dts	+	(Burki, 2015; GUoM), 2015; Htein et al., 2018;	-	This factor determines the ease with which populations can evacuate and find safety during emergency situations such as floods.	Potential proxy: Number of shelter places per 10000 people.

				Kawasaki et al., 2017; Reeder, 2019)			Includes schools, monasteries, and evacuation shelters.
Food security	Households that save food (%)	c_sfo	-	(Oo et al. 2018c, 2018a)	-	Flooding disrupts agriculture, affecting food availability. Saving food ensures that families will have sustenance to consume after a flood.	

Datasets:

UNEP Preview: http://preview.grid.unep.ch
WorldPop: http://www.worldpop.org.uk
Census 2014: http://themimu.info/census-data (spreadsheet: BaselineData_Census Dataset - Sr, District & Township_MIMU 16Jun2016 ENG.xlsx)
General Administration Department Survey 2016-17:

- Income: https://data.opendevelopmentmekong.net/dataset/general-administration-department-gad-2016-17--module-6-individual-income-section-prod2?type=dataset
- Population: https://data.opendevelopmentmekong.net/dataset/general-administration-department-gad-2016-2017---module-4-population-population-section-prod2?type=dataset
- Malaria/chronic disease: https://data.opendevelopmentmekong.net/dataset/general-administration-department-gad-2016-2017-module-7-health-most-disease-in-region-section?type=dataset
- Doctors: https://data.opendevelopmentmekong.net/dataset/general-administration-department-gad-2016-2017-module-7-health-personal-health-care-section?type=dataset
- Hospital beds: https://data.opendevelopmentmekong.net/dataset/general-administration-department-gad-2016-2017---module-7-health-hospital-section-prod2?type=dataset

The Armed Conflict Location & Event Data project (ACLED): https://acleddata.com/data-export-tool/
Vulnerability assessment 2018: http://themimu.info/vulnerability-in-myanmar (Spreadsheet: Datasets_Vulnerability Analysis in Myanmar_09Jul2018.xlsx)
The Malaria Atlas Project: https://malariaatlas.org/research-project/accessibility_to_cities/
Open Street Map: https://export.hotosm.org/en/v3/

Supplementary material II
Data analysis

Supplementary Material II provides additional information on outlier analysis and treatment, and multicollinearity assessment.

- **Outliers and winzorisation**: Box plots based on the interquartile range and skewness and kurtosis were used to identify outliers (where skewness >1 and kurtosis >3.5 indicate potential outliers (Hagenlocher et al. 2018)). There was a high number of data points outside the interquartile range, and indicators with high skewness and kurtosis. However, only nine points in total were determined to be outliers and errors based on the local expert knowledge of one of the authors. These were treated with winzorisation which is a common method to manage outliers (Damioli 2017). As the data was not treated with the intention to create normally distributed data (as this would alter the characterization of vulnerability and risk beyond what is the true situation in Myanmar), the median as a measure of central tendency for each indicator. Table B outliers which data points were treated and which value they were given.

Table B. Treated indicators and their values.

Indicator	**Treated value**	**From**	**To**	**Value**
s_pov	34303567	Seikkan	Yebyu	12357626
s_pov	26322559	Kyeemyindaing	Yebyu	12357626
s_pov	23616513	Kyauktada	Yebyu	12357626
s_pov	18114882	Magway	Yebyu	12357626
s_vec	509.32	Paletwa	Tanai	231.98
s_chr	2.281641	Palaw	Aunglan	1.558724
s_fhh	55.05	Thayetchaung	Amarapura	40.97
s_fhh	48.41	Patheingyi	Amarapura	40.97
c_doc	248.09	Oke Ta Ra Thi Ri	Cocokyun	8.97

- Multicollinearity assessment: A multi-collinearity assessment was conducted to determine if there were any redundant indicators. Using Kendall's Tau suitable for non-normal data (Puth et al. 2015), and two tailed significance, no issue of collinearity was detected based on a threshold of ±0.9. Table C outlines the results from the analysis.

TABLE C: Results of multicollinearity assessment using Kendall's Tau using SPSS (IBM SPSS Statistics)

Correlations

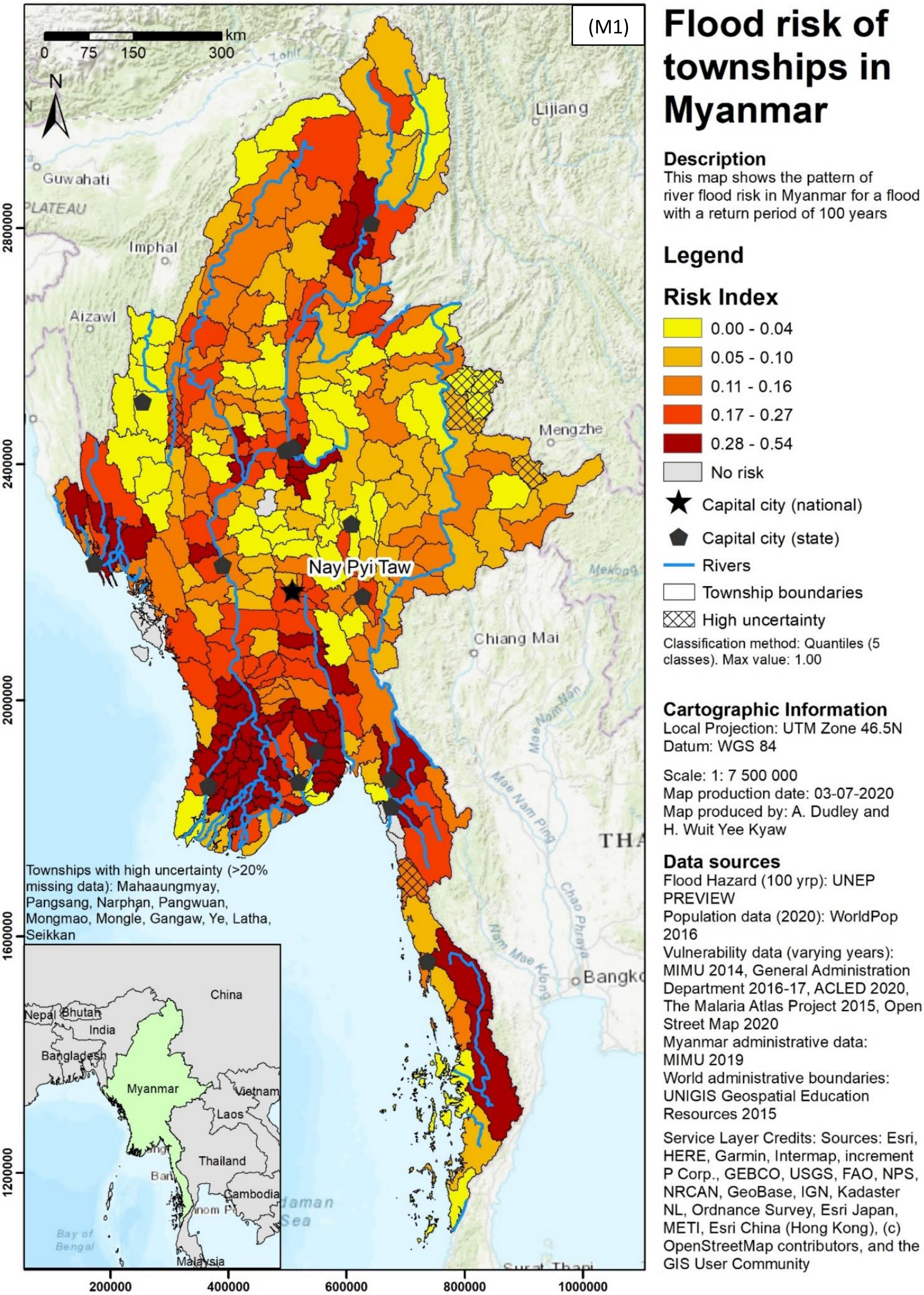
			e_soc	s_dep	s_pov	s_dis	s_vec	s_chr	s_fhh	s_con	s_san	s_dri	s_wfl	s_ttc	s_daw	c_ati	c_lit	c_dens	c_boa	c_doc	c_bed	c_aes
Kendall's tau_b	e_soc	Correlation Coefficient	--																			
		Sig. (2-tailed)																				
	s_dep	Correlation Coefficient	-0.051	--																		
		Sig. (2-tailed)	0.168																			
	s_pov	Correlation Coefficient	0.026	-.368**	--																	
		Sig. (2-tailed)	0.480	0.000																		
	s_dis	Correlation Coefficient	0.036	.271**	-.120**	--																
		Sig. (2-tailed)	0.327	0.000	0.001																	
	s_vec	Correlation Coefficient	0.003	.308**	-.268**	.123**	--															
		Sig. (2-tailed)	0.932	0.000	0.000	0.001																
	s_chr	Correlation Coefficient	.212**	0.034	0.024	.094*	.091*	--														
		Sig. (2-tailed)	0.000	0.351	0.514	0.011	0.015															
	s_fhh	Correlation Coefficient	-0.046	-.096**	.175**	-.085*	-.100**	0.069	--													
		Sig. (2-tailed)	0.214	0.009	0.000	0.021	0.008	0.063														
	s_con	Correlation Coefficient	-0.026	.190**	-.215**	0.013	.182**	-0.017	0.040	--												
		Sig. (2-tailed)	0.546	0.000	0.000	0.761	0.000	0.687	0.347													
	s_san	Correlation Coefficient	0.016	-.412**	.239**	-.168**	-.259**	0.011	.233**	-.196**	--											
		Sig. (2-tailed)	0.662	0.000	0.000	0.000	0.000	0.757	0.000	0.000												
	s_dri	Correlation Coefficient	0.044	-.344**	.250**	-.233**	-.177**	0.024	.246**	-.187**	.412**	--										
		Sig. (2-tailed)	0.234	0.000	0.000	0.000	0.000	0.517	0.000	0.000	0.000											
	s_wfl	Correlation Coefficient	.144**	.106**	-.110**	.083*	0.055	0.053	-.159**	0.015	-.309**	-.152**	--									
		Sig. (2-tailed)	0.000	0.004	0.003	0.025	0.147	0.151	0.000	0.728	0.000	0.000										
	s_ttc	Correlation Coefficient	-0.046	.450**	-.374**	.230**	.450**	-0.066	-.245**	.202**	-.343**	-.312**	.089*	--								
		Sig. (2-tailed)	0.218	0.000	0.000	0.000	0.000	0.076	0.000	0.000	0.000	0.000	0.016									
	s_daw	Correlation Coefficient	.094*	-0.042	.110**	0.012	-.140**	.084*	0.006	-0.044	0.026	0.004	0.028	-.144**	--							
		Sig. (2-tailed)	0.011	0.259	0.003	0.742	0.000	0.022	0.869	0.306	0.486	0.924	0.453	0.000								
	c_ati	Correlation Coefficient	-.108**	-.439**	.242**	-.269**	-.208**	-0.053	.259**	-.104*	.406**	.301**	-.289**	-.339**	0.007	--						
		Sig. (2-tailed)	0.004	0.000	0.000	0.000	0.000	0.153	0.000	0.015	0.000	0.000	0.000	0.000	0.842							
	c_lit	Correlation Coefficient	.140**	-.482**	.390**	-.193**	-.282**	0.052	.191**	-.303**	.428**	.387**	-.165**	-.410**	.079*	.290**	--					
		Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	0.161	0.000	0.000	0.000	0.000	0.000	0.000	0.031	0.000						
	c_dens	Correlation Coefficient	.091*	-.423**	.339**	-.130**	-.445**	.078*	.185**	-.150**	.315**	.365**	-0.056	-.581**	.113**	.309**	.366**	--				
		Sig. (2-tailed)	0.014	0.000	0.000	0.000	0.000	0.034	0.000	0.000	0.000	0.000	0.129	0.000	0.002	0.000	0.000					
	c_boa	Correlation Coefficient	.366**	.094*	0.019	.183**	0.045	.196**	-.080*	-0.072	-.118**	-.158**	0.067	0.040	.099**	-.197**	.108**	-.077*	--			
		Sig. (2-tailed)	0.000	0.011	0.603	0.000	0.231	0.000	0.030	0.093	0.001	0.000	0.070	0.284	0.007	0.000	0.004	0.037				
	c_doc	Correlation Coefficient	-.108**	-0.036	0.020	-0.016	.105**	-0.060	0.007	-0.050	.132**	0.043	-0.050	.085*	-0.030	0.030	0.029	-.130**	-0.035	--		
		Sig. (2-tailed)	0.004	0.333	0.583	0.672	0.005	0.106	0.846	0.243	0.000	0.241	0.180	0.023	0.412	0.411	0.430	0.000	0.344			
	c_bed	Correlation Coefficient	-.149**	-0.035	0.002	-0.044	.117**	-.141**	0.015	0.009	.118**	0.053	-.193**	.142**	-.119**	.119**	-0.013	-.099**	-.134**	.386**	--	
		Sig. (2-tailed)	0.000	0.341	0.949	0.238	0.002	0.000	0.688	0.842	0.001	0.151	0.000	0.000	0.001	0.001	0.718	0.007	0.000	0.000		
	c_aes	Correlation Coefficient	-.093*	.254**	-.148**	0.020	.330**	0.041	-0.038	0.039	-.189**	-.147**	.121**	.280**	-0.054	-.104**	-.223**	-.316**	0.020	.092*	-0.023	--
		Sig. (2-tailed)	0.012	0.000	0.000	0.587	0.000	0.264	0.307	0.357	0.000	0.000	0.001	0.000	0.144	0.005	0.000	0.000	0.584	0.013	0.526	

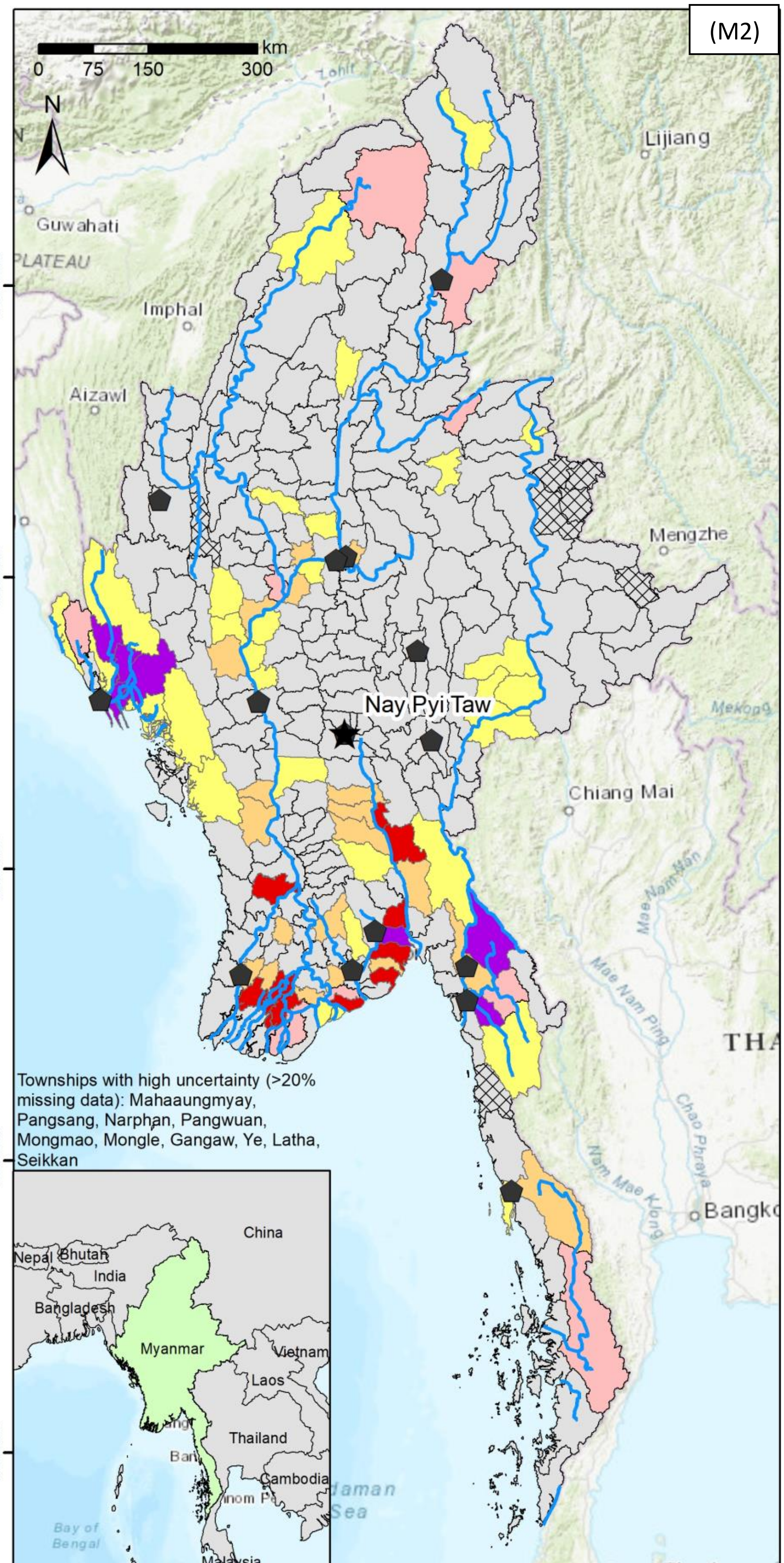
**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Supplementary Material III
Maps

Supplementary Material III contains duplicates of maps from the text of (M1) risk from method one, (M2) risk from method two, and (M3) hazard, exposure, vulnerability, and risk (method one).





Comparison of different degrees of flood exposure and vulnerability in Myanmar

Description

This map shows the spatial relationship between river flood exposure (exp) and vulnerability (vul) by the intersection of their quantiles for townships in Myanmar

Legend

- VH Exp & VH Vul
- VH Exp & H Vul
- H Exp & H Vul
- H Exp & M Vul
- M Exp & M Vul

Quantile 5: Very High (VH)
Quantile 4: High (H)
Quantile 3: Medium (M)
Quantiles from map "Flood vulnerability of townships in Myanmar" and "Flood exposure of townships in Myanmar"

- Capital city (national)
- Capital city (state)
- Rivers
- Township boundaries
- High uncertainty

Cartographic Information

Local Projection: UTM Zone 46.5N
Datum: WGS 84

Scale: 1: 7 500 000
Map production date: 03-07-2020
Map produced by: H. Wuit Yee Kyaw and A. Dudley

Data sources

Flood Hazard (100 yrp): UNEP PREVIEW
Population data (2020): WorldPop 2016
Vulnerability data (varying years): MIMU 2014, General Administration Department 2016-17, ACLED 2020, The Malaria Atlas Project 2015, Open Street Map 2020
Myanmar administrative data: MIMU 2019
World administrative boundaries: UNIGIS Geospatial Education Resources 2015

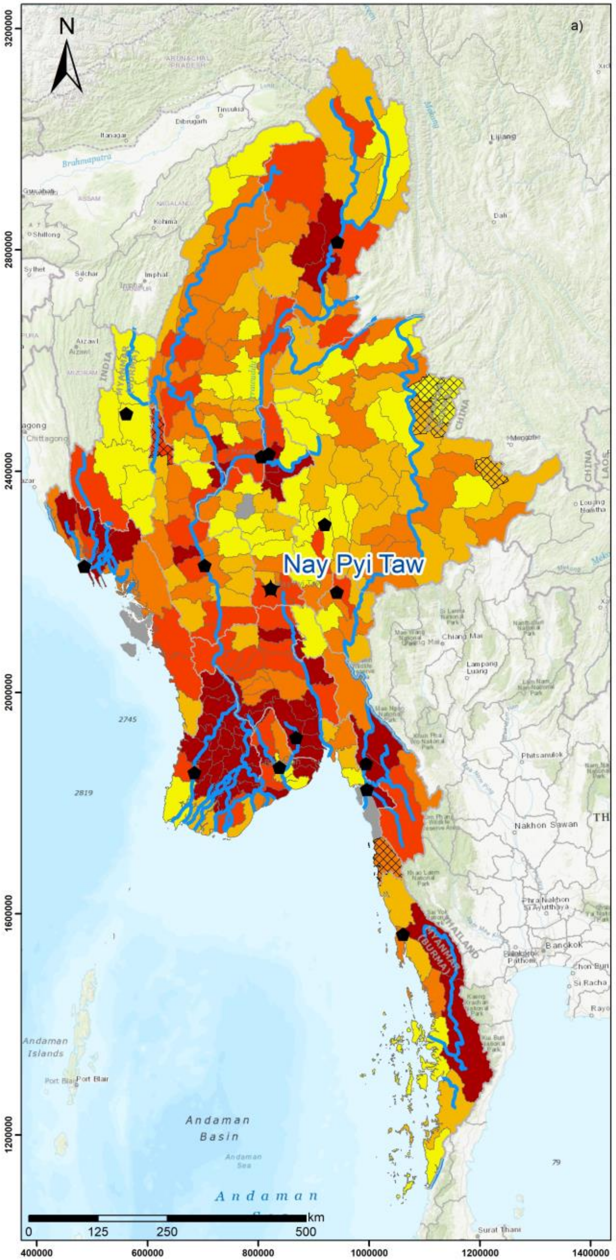
Service Layer Credits: Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), (c) OpenStreetMap contributors, and the GIS User Community

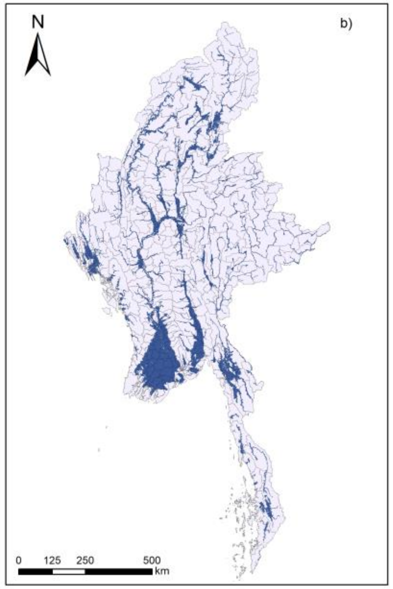
(M3)

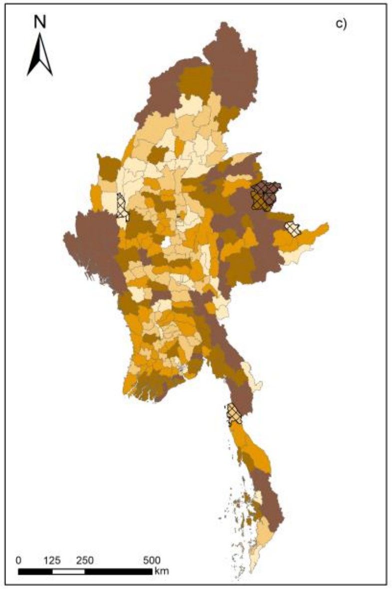
Patterns of flood risk in different townships of Myanmar

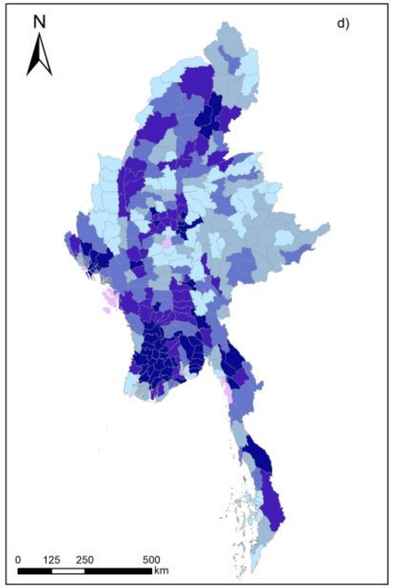
Description

This map shows patterns of flood risk in panel a), flood hazard in panel b), vulnerability in panel c), and exposed population in panel d) respectively within different townships of Myanmar.









Legend

a) Risk

- 0.00 - 0.04
- 0.05 - 0.10
- 0.11 - 0.16
- 0.17 - 0.27
- 0.28 - 0.54
- No Risk

c) Vulnerability

- 0.33 - 0.44
- 0.45 - 0.47
- 0.48 - 0.49
- 0.50 - 0.52
- 0.53 - 0.69

d) Exposure

- 0.00 - 0.08
- 0.09 - 0.20
- 0.21 - 0.35
- 0.36 - 0.58
- 0.59 - 1.00
- No Exposure

Classification Scheme: Quantile intervals (5 classes). Max value: 1.00.

- ★ Capital city (national)
- ⬟ Capital cities (state)
- Rivers
- High uncertainty
- Flood extent 100 year return period
- Myanmar township boundaries

Townships with high uncertainty (>20% missing data): Mahaaungmyay, Pangsang, Narphan, Pangwaun, Mongmao, Mongla, Gangaw, Ye, Latha, Seikkan

Cartographic Information
Local Projection: UTM Zone 46.5 N
Datum: WGS 84

Data sources
Flood Hazard (100 yrp): UNEP PREVIEW
Population data (2020): WorldPop 2016
Vulnerability data (varying years): MIMU 2014, General Administration Department 2016-17, ACLED 2020, The Malaria Atlas Project 2015, Open Street Map 2020
Myanmar administrative data: MIMU 2019
World administrative boundaries: UNIGIS Geospatial Education Resources 2015

Scale (Main Map): 1: 6000000
Map Production **Date** : 04-07-2020
Map Produced by: H.Wuit Yee Kyaw and A.Dudley

Service Layer Credits: Sources: Esri, GEBCO, NOAA, National Geographic, Garmin, HERE, Geonames.org, and other contributors
Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), (c) OpenStreetMap contributors, and the GIS User Community