Sierra Leone:
Shock Responsive Social Protection
Global Risk Financing Facility

Vulnerability and Risk Analysis
Final Report

February 17, 2022

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1. Introduction

Sierra Leone is one of the most vulnerable countries to climate change in West Africa and among the Least Developed Countries (LDCs), facing impacts associated with floods, landslides, and other climate hazards. As one of the poorest countries in the world, climate-related risks threaten the country's economic sectors and can exacerbate environmental degradation. Moreover, the impacts of the 2014-2016 Ebola virus outbreak, and more recently, the COVID-19 pandemic, have hindered progress towards ensuring socio-economic development and greater resilience against climate hazards.

As with other West African countries, the Sierra Leonean economy is highly reliant on agriculture, which provides livelihoods for three-quarters of the population and over half of the country's gross domestic product (USAID, 2016). However, a significant portion of agriculture continues to be rainfed and focused on smallholdings, highlighting the sensitivity of livelihoods to climate hazards such as floods, landslides, and droughts.

Floods and landslides are among the major hazards impacting communities in Sierra Leone. Historically, heavy rainfall events that trigger floods and landslides have destroyed houses, road networks, and farmland – all of which significantly impact the well-being of at-risk communities. Other impacts are also potentially devastating: for example, stagnant pools of water increase the risk of mosquito infestations and malarial infection. The abundance of contaminated water with limited Water, Sanitation and Hygiene (WASH) facilities also means communities are more exposed to diseases such as diarrhea and cholera. In addition, floods and landslides can destroy food crops, resulting in increased malnutrition among young children.

According to data reported in ReliefWeb – the UN humanitarian information system and the most comprehensive database on humanitarian impacts associated with hazards – there have been at least six major flood events since 2000 (Figure 1), with the highest number of people impacted in 2015 and 2005. From the limited historical data available, there is no clear indication of whether floods are becoming more frequent or more intense. However, climate projections suggest that the West African rainy season is expected to become shorter and more intense with heavy rainfall events becoming the norm towards the end of the 21st century (cf. Seneviratne et al., 2021), highlighting the urgent need to better understand flood and landslide risk and use such information to improve disaster management efforts.

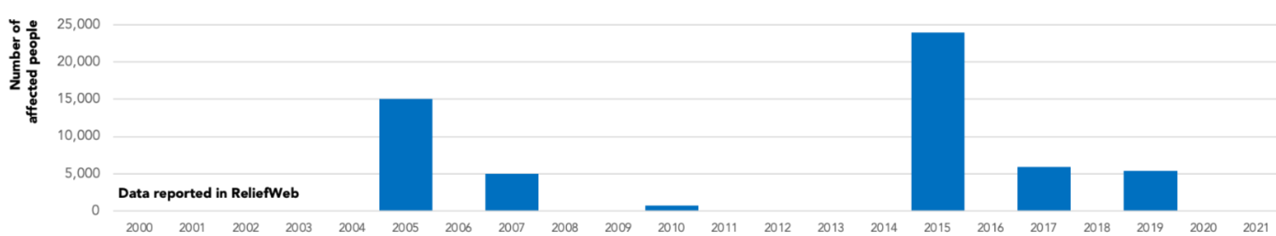

Figure 1 Overview of the population impacted by floods over time. [Source: ReliefWeb, 2021 (reports from various years)]

Social protection can protect the poor from shocks and stresses, prevent households from falling into poverty, and promote climate-resilient livelihoods. The World Bank's Global Risk Financing Facility (GIIF) is implementing the Shock Responsive Social Protection project (SRSP) in Sierra Leone. The goal of the project is strengthening the capacity of National Commission for Social Action (NACSA) to provide earlier and more reliable response and recovery to climate and disaster shocks. One of the main themes of the SRSP involves a comprehensive mapping and analysis of household vulnerability to shocks focusing on flood and landslide risk. The analysis is instrumental for the operation and monitoring of a shock-responsive social protection system as it informs prioritization and targeting in the event of a shock. This report summarizes the results of the risk and vulnerability analysis. This analysis will inform subsequent themes of the project including contingency planning, trigger design, and resilience programming.

2. Methods and Data

a. Framework

In the context of disaster management and climate change adaptation, risk is defined as the probability of occurrence of hazardous events or trends multiplied by the impacts if these events or trends do take place (UNISDR, 2019). Risk results from the interaction of climate hazards (for this work, the focus is on floods and landslides), exposure (i.e., the presence of people, infrastructure, and assets in areas that could be adversely affected by climate hazards), and vulnerability (i.e., the socio-economic conditions that determine the propensity of a given population or system to be affected by a climate hazard). This is summarized in Figure 1 below (IPCC, 2012); additional definitions are provided in Table 1.

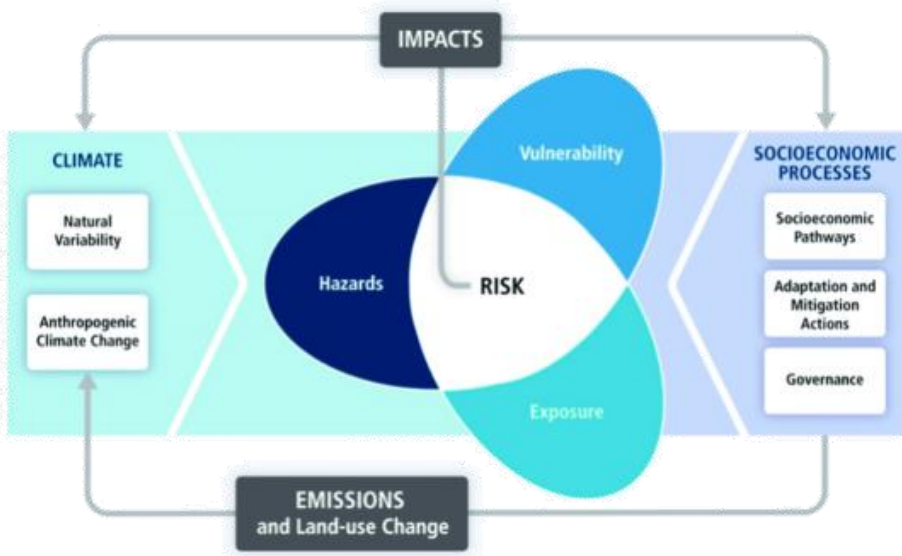

Figure 2 In disaster risk management and climate change adaptation practice, risk is defined as a function of hazards, exposure, and vulnerability. [Source: Field et al., 2012]

Table 1. Definitions of key terms: risk, vulnerability, sensitivity, adaptive capacity, exposure, and hazard

Term	Definition
Risk	The probability of having adverse consequences resulting from hazardous events on human society and natural ecosystems
Hazard	The potential occurrence of a harmful event may cause loss and damage to societal and environmental resources
Exposure	The existence of human society, economic activities, natural ecosystem, and physical communal assets that probably be adversely affected
Vulnerability	The susceptibility or sensitivity of exposures to the impact of hazards in the absence of their capacity to cope and adapt
Sensitivity	The characteristics of a system or community adversely or beneficially affected by a given hazards. Sensitivity is one of the sub-components of vulnerability.
Adaptive capacity	The ability of communities or systems to adjust to hazard to moderate potential damages. Adaptive capacity is one of the sub-components of vulnerability.

b. Hazard

Hazards refer to climatic trends or events that result in impacts such as loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems, and environmental resources (Field et al., 2012). For the purposes of this analysis, the hazards of interest are floods (including pluvial and fluvial floods) as well as landslides. The choice of these three was motivated by the fact that (i) unlike other disasters they have a potential predictability which can be used to anticipate their impacts and (ii) they are High-Impact Weather events accounting for around 30% of historical disaster impacts in the country (DesInventar - Profile). The 2017 landslide for example killed around 1,100 people.

Pluvial flood is defined as a flood caused by an extreme rainfall event independent of an overflowing water body. Fluvial (also called riverine) floods are caused by the water level in a river, lake, or stream rising and overflowing onto the surrounding banks, shores, and neighboring land (it, therefore, is not necessarily linked to a direct rainfall effect). As for landslides, they are defined as the movement of a mass of rock, debris, or earth down a slope (Hungr et al., 2014).

Flood analysis. Sierra Leone is a data-scarce country. Observed daily rainfall data were available only at one station and for a relatively short period of time (10 years). No water level data was obtained for this study. Therefore, we used publicly available datasets on rainfall and river discharge estimates derived from hydrological models to quantify flood hazards. Since these datasets have a relatively high spatial resolution, analysis can be disaggregated at the third administrative level (chiefdom/ward). However, given the lack of hydrogeological data available at this spatial resolution, the landslide results are presented at the district level. The corresponding flood results at the district level are shown in Annex 3.

***Rainfall data*.** We use rainfall data derived from publicly available Earth observation products. After reviewing different criteria, such as longevity of the satellite missions, spatial and temporal resolutions, acceptance in the region (including by the Pan-African ACMAD center), and accuracy of rainfall estimates in Sierra Leone, we selected two products: Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) - a blended satellite and weather station product - and Tropical Applications of Meteorology using SATellite (TAMSAT). The choice of more than one dataset is aimed at capturing the uncertainty in remote-sensed precipitation estimates in the tropics. Both datasets have a daily temporal resolution with CHIRPS having a grid of 0.05° x 0.05° and TAMSAT 0.0375° x 0.0375°. The analysis is performed over a common period of 1983-2020**.**

Hydrological data. Unlike precipitation, gridded hydrological estimates (including river discharge and water level) data are limited. Water level data were obtained from FATHOM-global, a two-dimensional hydrodynamic model (Simpson et al. 2015). Data were already preprocessed and consisted of flood return levels for different periods (see below for a definition of return levels) at a horizontal resolution of about 90m x 90m. An additional candidate dataset was explored: the Global Flood Awareness System (GloFAS) reanalysis (Harrigan et al. 2020). It combines in-situ and remote data with numerical models to generate an optimal estimation of river discharge. GloFAS version 2.1 at a daily temporal resolution with a horizontal grid of 0.1° x 0.1° is used. It was only used to describe the hazard over the 1983-2020 period (but discarded in the final risk analysis) as it shows poor skill in small catchments like those found in Sierra Leone.

Method. Two hazard metrics are included in the analysis: one addresses the full distribution of the hazard and is taken as the average yearly total for rainfall and the average daily value for GloFAS river discharge, while the second metric focuses on the extremes of the hazard. As FATHOM data do not contain an information on the average daily value, return levels were more used in the analysis for consistency purposes. Return levels for a given period represent the intensity of the hazard, which is expected to occur on average once within the specified time window. Thus, for example, a five-year return level of 50 mm for rainfall means that, on average, a rainfall event of intensity equal to or higher than 50 mm is expected to occur once every five years.

Landslide analysis.

Data. Several data are necessary to understand the landslide hazard in each country. Three main types of data were used in this study: (i) Land use land cover (LULC) data provided by the FAO (accessible from https://data.review.fao.org/map/catalog/srv/api/records/973fdcbe-c347-47a7-9af7-e2e57729a35b) and which is a vector version (ESRI shape) of the Globcover archive that was published in 2008. (ii) Land degradation (erosion) data over the 2001-2012 period prepared by WFP (https://geonode.wfp.org/layers/geonode:sle_ica_landdegradation_geonode_20170517/metadata_detail) based on a HQ OSEP GIS Analysis of NASA MODIS. (iii) Rainfall data obtained by a merging of CHIRPS and TAMSAT.

Method. The method mainly consists in the combination of the three data listed above to generate a final hazard map. As LULC and land degradation data were not available at the third administrative level, the analysis was performed only at the district level.

c. Exposure

Exposure refers to the range of elements in an area where hazard events may occur (UNISDR 2004, 2009b). Therefore, exposure considers both the hazard and the people who may be affected. For this analysis, we consider exposure to be the number of people living in a hazardous area.

Population data. The most reliable population estimates at the third administrative division (chiefdom/wards) are available in the 2015 Census.

Method. To calculate flood exposure, we multiply population estimates with hazard metrics to determine the exposure. We use the return level metric as it is the only one that can be derived across all datasets, thereby enabling comparison. A one-in-five-year return level has been retained here, as other return levels yield similar spatial patterns. Before summing the metrics of hazard occurrence and affected people, it is essential to first do a normalization, i.e., harmonizing values to a common scale. The following formula gives the normalized value of a given metric:

$$X_{normal} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

where X_{normal} is the normalized metric at a given point in space, Xi the raw value, X_{min} and X_{max} the minimum and maximum values.

The exposure is then taken as the average of the normalized metrics of hazard occurrence and affected population:

Exposure= (Hazard + Population size)/2

Note that the pluvial (based on rainfall) and fluvial hazards (based on river discharge or water level) are reported separately.

For landslides, each of the three-hazard components (LULC change, erosion change and rainfall five-year return levels) is first normalized using (1) before merging them with the population size using (2).

d. Vulnerability

Vulnerability refers to the socio-economic conditions that render a population (or a subset of a population) susceptible to impacts associated with hazards – for example, families living in houses constructed with poor materials are more likely to be negatively impacted compared to families living in higher quality housing. For this analysis, we present two potential approaches to define vulnerability. The first approach incorporates various indicators from the 2015 Census, fusing them in the composite vulnerability index (CVI). In contrast, the second approach is based on the multidimensional poverty index (MDPI).

Composite vulnerability index (CVI) based on multiple indicators. For composite vulnerability, we first identified relevant indicators from the 2015 Census, guided by an in-depth literature review and the IPCC risk framework. The rationale for selecting indicators from one database (i.e., the 2015 Census) was threefold: (1) the Census collects data at the household level, enabling highly granular analysis; (2) the Census occurs regularly every ~10 years, allowing for the vulnerability and risk analysis to be updated once the data are available; and (3) the Census collects information in uniform manner allowing for comparison across indicators without issues related to sampling bias or data interpretation that may arise when dealing with multiple data sources.

Vulnerability based on poverty indicators (MDPI). Poverty rates in Sierra Leone are extremely high; indeed, Sierra Leone ranks 182 out of 189 countries according to the 2020 Human Development Index. The COVID-19 pandemic and associated lockdowns are projected to exacerbate poverty rates in both urban and rural areas.

Method. Chiefdom-level CVI is quantified through a PCA (principal component analysis)-based index, with a value of 1 representing the highest vulnerability and a value of 0 representing the lowest vulnerability level. Initially, a total of 23 indicators were selected; and after testing for autocorrelation, a final list of 13 indicators was identified (Table 2; Annex 1)[1].

A principal component analysis provides potential advantages in the aggregation of spatially explicit variables. For instance, when the indicators are correlated then the principal components will capture more of the total variability in the data than any single variable (cf. Abson et al., 2012). Moreover, PCA provides a framework to reduce a large set of individual indicators to a small number of components without compromising richness in data. Details on the PCA are included in Annex 2.

Table 2. Indicators and rationale for inclusion in the CVI analysis.

Indicator	Rationale
Adult illiteracy	It is expected that literate people are less vulnerable because they can access better job opportunities and therefore greater possibilities to earn better incomes (Ghosh and Ghosal, 2021).
Dependency ratio	In households with a high dependency ratio, that economically active individuals have many other family members to support, and thus, resources for coping with natural hazards are more limited This contributes to higher vulnerability levels during flood and landslide events (Sam et al., 2017).
Disabled population	People with disability experience multidimensional inequalities. For instance, disabilities pose barriers to accessing health, education, and employment. As a result, populations with disabilities experience heightened vulnerability to flood and landslide events (Gaskin et al., 2017).
Households engaged in animal husbandry	Animal husbandry is vulnerable to extreme changes in temperature or rainfall; for instance, cattle is more susceptible to diseases such as foot-and-mouth disease during heavy rainfall events (Rao, 2021).
Households engaged in cropping	Communities whose primary livelihood depends on agricultural activities are more sensitive to climate events; for instance, major flood events can result in waterlogging of crops which can then translate to income loss (Adu et al., 2018; Wichern et al., 2019).
Households engaged in fisheries	The ability of households to engage in fisheries is also impacted by heavy rainfall events and landslides, which can destroy critical livelihood assets (such as fishing boats) or result in contamination of water bodies, thereby limiting availability of fish (Ding et al., 2017).
Households with poor access to water	Access to safe water for personal consumption is critical during a climate hazard such as a flood or a landslide. Households with limited or no access to improved drinking water sources are more likely to suffer from health conditions, such as diarrhea, which make them vulnerable to the impacts of climate hazards (Grasham et al., 2019; Shah et al., 2020).
Houses with poor roof material	Housing quality is a key factor determining the level of vulnerability to climate hazards. Roofs built from lower quality and less durable materials – such as thatched roofs or roads built from tarpaulin – are less able to withstand heavy rainfall events and landslides (Fatemi et al., 2020).
Houses with poor floor type	As with roof types, floor types can impact the ability of a house to withstand heavy rainfall events. Houses with floors made from wood or mud are more likely to be damaged to destroyed than houses with floors constructed from tiles or concrete (Adebimpe et al., 2018).
MDPI	Poorer households have less resources to manage impacts associated with a disaster (Alamgir et al., 2020; Kawasaki et al., 2020).
Population deprived of healthcare	Public health risks are among the most severe in the aftermath of a flood or a landslide. Households with limited (or no) access to healthcare facilities are at greater risk of experiencing adverse impacts (Shah et al., 2020).

[1] Other possible databases are included in the Data Inventory; however, indicators from these databases were not included in this analysis for the reasons highlighted here – namely, the possibility to use regularly updated data, the possibility to use high resolution household data, and consistency in data collection and interpretation methods.

Unemployed population	Unemployed populations have limited access to resources to manage the impacts of climate hazards because lower access to income affects the ability to respond and recover to floods and landslides (Munyai et al., 2019; Ullah et al., 2021).
Female-headed households	Female-headed households tend to be less resilient, due to other external factors like limited income-earning possibilities (Alhassan et al., 2019).

e. Risk

Finally, overall risk is calculated through summing vulnerability with exposure, and normalizing.

Pluvial flood risk= (Pluvial hazard exposure + Vulnerability Index) /2
Fluvial flood risk= (Fluvial hazard exposure + Vulnerability Index) /2
Landslide risk= (Landslide hazard exposure + Vulnerability Index) /2

3. Results: Flood and Landslide profile

a. Flood and Landslide Hazards

i. Pluvial Floods

The average annual rainfall totals range from ~1800 to close to 4000 mm across Sierra Leone (Fig. 3). The north and east of the country receive the least rainfall whereas the peak of rainfall is observed near the Atlantic coast in the west and south. A second peak with annual totals 3000 mm is observed in the center of the country (around the district of Tonkolili). Both CHIRPS and TAMSAT datasets share a similar spatial distribution. It is however perceptible that the rainfall totals in TAMSAT are slightly lower than in CHIRPS, especially in the central parts of the country.

The seasonal distribution indicates that the rain falls mostly between April and November with August being the peak (monthly totals close to 1000 mm near the coast). The winter months of December to March are the driest as they receive mostly less than 50 mm each.

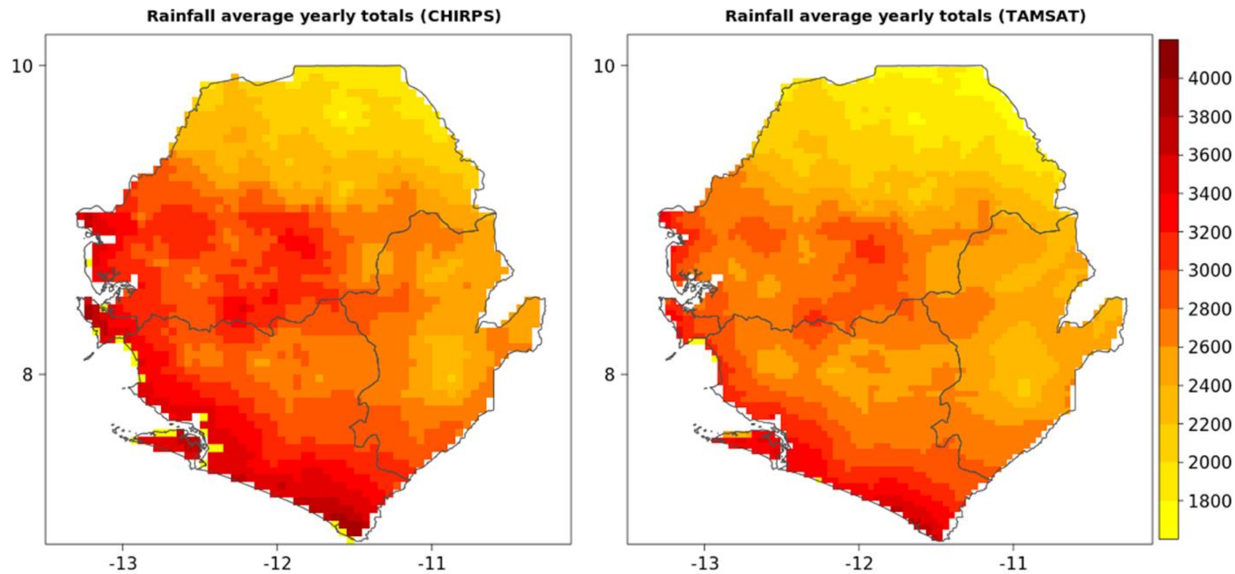

Figure 3. Annual rainfall in Sierra Leone based on (left) CHIRPS and (right)TAMSAT (in mm)

Extreme rainfall. Here, five-year return levels (RL5 hereafter) are used to gain insight into the intensity of extreme rainfall events i.e., which have the potential to cause severe flash floods. The interest is in the spatiality (how the magnitude of RL5 varies spatially across the country) and seasonality (how the occurrence of RL5 varies throughout the year).

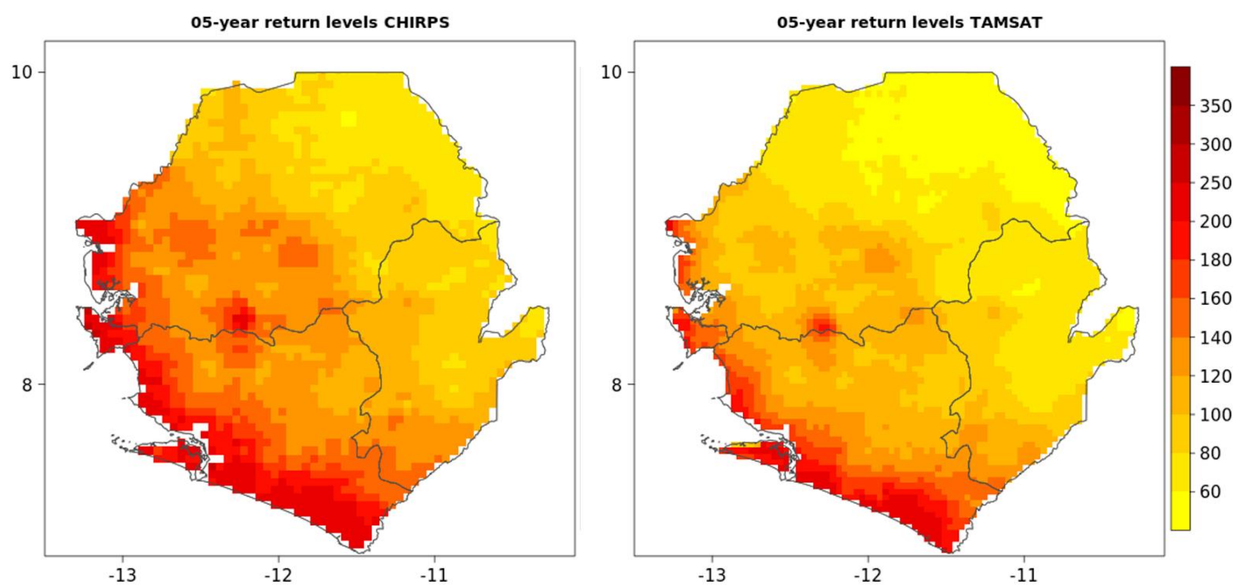

Figure 4. Five-year return levels of daily precipitation in Sierra Leone based on (left) CHIRPS and (right) TAMSAT (in mm).

The spatial distribution of extreme precipitation (above RL5) in Sierra Leone (Fig. 4) matches well with that of annual total. The highest values (above 200 mm/day) are found near the Atlantic coast. The southwest-northeast gradient is also well marked such that the lowest values are found near the northern border with Guinea. The second order peaks observed in central Sierra Leone with annual totals are less apparent with extreme precipitation, spreading over smaller areas (especially in TAMSAT). From a temporal point of view, extreme precipitation occurs in summer during the peak of the West African monsoon. July and (mostly) August are indeed the months with the highest numbers of heavy rainfall events. RL5 events are more recurrent in the north of the country as they are in lower intensity there. Using a percentile metric (e.g., percentile 95 (P95)) for extreme precipitation gives the same frequency but highlights some differences in seasonality (Fig. 5). Thus, the southernmost parts of the Southern Province receive above P95 rainfall events in July whereas the other regions receive similar levels of rainfall in August. Also, in September, unlike in all the other months, the frequency of above P95 precipitation is higher in the northeast than anywhere else in the country. This is consistent in CHIRPS and TAMSAT and should therefore be taken into consideration in the planning of interventions across the country.

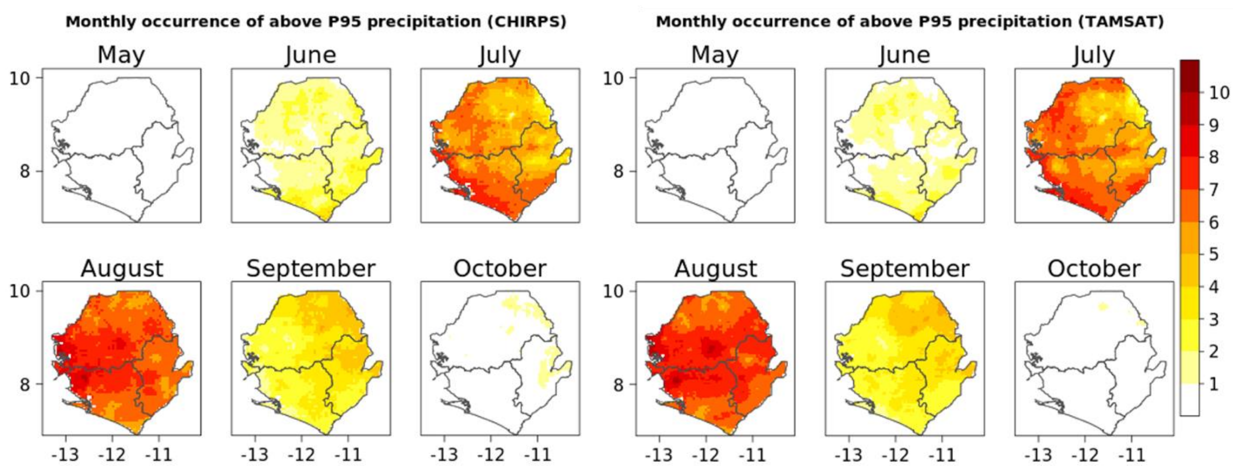

Figure 5. Monthly occurrence of precipitation of intensity above the 95th percentile during the rainy season months based on (left) CHIRPS and (right) TAMSAT. A monthly occurrence of 1 means that one above P95 precipitation event is recorded on average in the month.

In addition to the single extreme rainy events, it is important to consider spells with consecutive high rains (extremely wet spells). Extremely wet spells are subjectively defined here as periods of three or more consecutive days where daily rainfall reaches or exceeds P95 on each day. Their spatial distribution and frequency are sensible to the dataset (Fig. 6). In CHIRPS, they are the most frequent in the westernmost parts of the country, in the districts of Port Loko, Western Areas (urban and rural) and Moyamba with a frequency rarely exceeding six per decade. On the other hand, in TAMSAT, they are the most frequent in the south of the country, with an additional area of maximum in the center. TAMSAT wet spells are also more frequent, exceeding eight per decade in large areas across southern Sierra Leone.

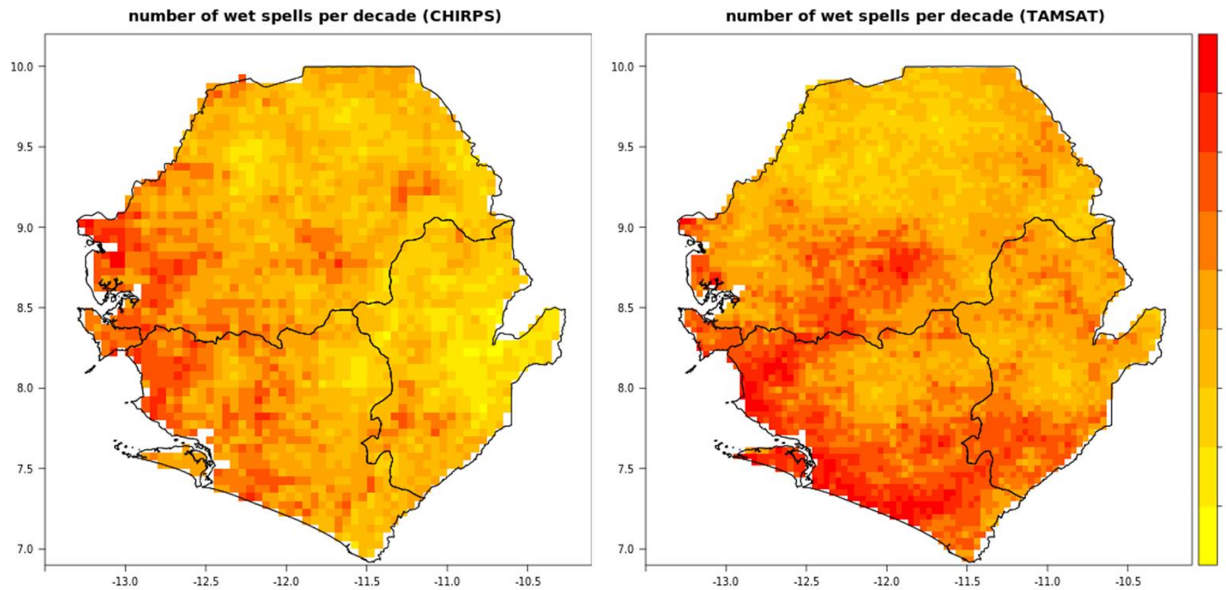

Figure 6. Frequency of occurrence of wet spells (in number events per decade) in Sierra Leone based on (left) CHIRPS and (right) TAMSAT.

ii. Fluvial floods

The fluvial flood hazard is described here mostly using river discharge from GloFAS reanalysis whose skill is reduced in limited catchments like those found in Sierra Leone, and water level from FATHOM.

Average river discharge. Sierra Leone is crossed by five main rivers which drain most of the country's land. They include the Little Scarcies, Rokel, Jong, Sewa and Moa rivers. Consistent with rainfall patterns, there is a marked seasonality of river discharge in the country. From December to May, the river discharges are exceptionally low across the country, not exceeding 5 m^3/s in the most important rivers. From June and with the first rains, there is a progressive replenishment of the rivers leading to increasing flows. The annual peaks are recorded between August and October with the average daily discharge during these months exceeding 30 m^3/s according to GloFAS.

Extremes of river discharge and water level. The extremes of fluvial floods are characterized using return levels of river discharge for GloFAS and water level for FATHOM.

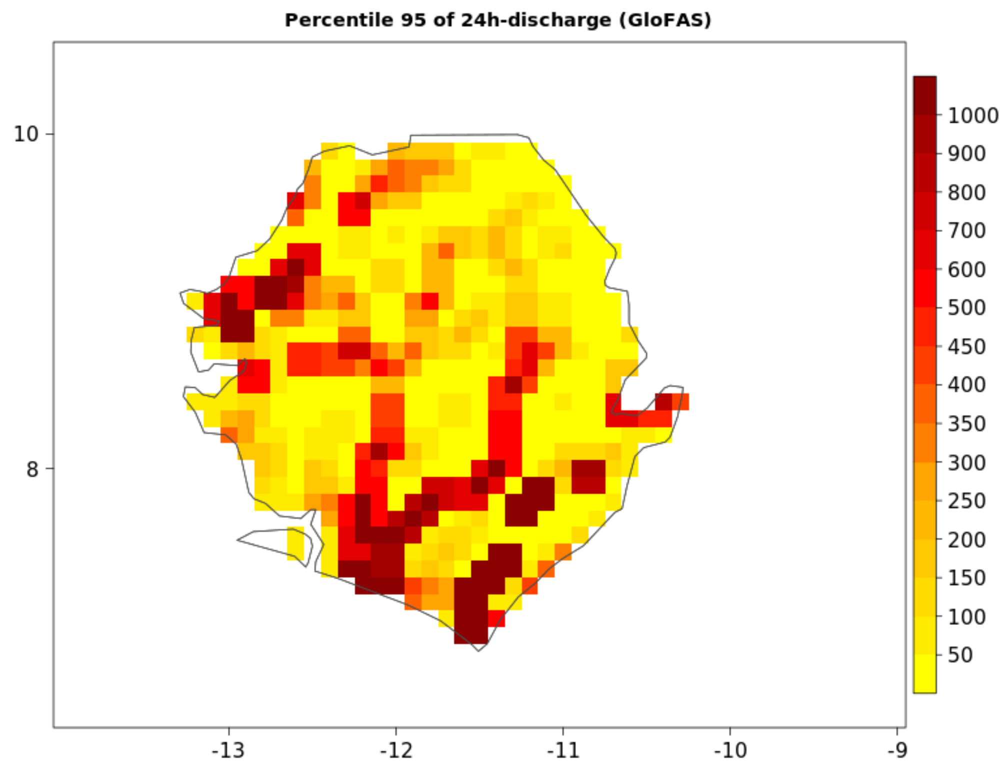

Figure 7. Percentile 95 of river discharge based on GloFAS (in m^3/s).

As with rainfall, several metrics are used to characterize extreme hydrological events in Sierra Leone. Using P95, the largest values are observed in the Moa, Sewa and Little Scarcies rivers where they exceed 1,000 m^3/s (Fig. 7). The highest values are observed in their lower reaches, close to the Atlantic Ocean. August and September are the months with the largest occurrences of extreme discharge in Sierra Leone. This corresponds to a one-month delay compared with the timing of rainfall extremes (observed in July and August). A marked difference in spatiality in the occurrence of discharge extremes is also observed. In August, the largest discharges are more frequent in the northwestern half of the country whereas in September they are the highest and are mostly encountered in the center and east of the country (agreeingly with the rainfall distribution). It is worth mentioning that in September extreme discharge days are significantly less than in August near the western coast.

FATHOM return level data are used to understand the extremes of water level in Sierra Leone's water bodies. Apart from the (expected) change in the actual values of the return levels, no significant difference is observed when comparing different time periods. Therefore, as with the rainfall, only RL5 values are discussed here. Overall, across the country, one-in-five-year events correspond to water levels below 2 m (Fig. 8). RL5 values can, however, become significantly important in places. Thus, in the Sewa river, RL5 values reach 4m in the most flood prone areas (in the lower reaches), 5 to 6 m in the Moa River and 7 m in the Little Scarcies.

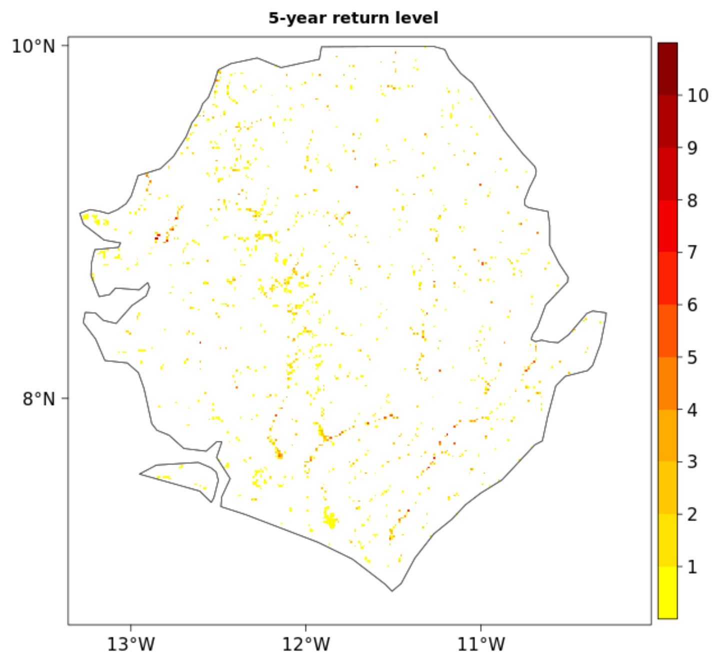

Figure 8. Five-year return levels (in meters) of water levels based on FATHOM

iii. Landslides

The LULC map (Figure 9) shows the land cover in Sierra Leone. The dominant land cover is swamp forest in the north and central parts of the country. Mangroves are spread all over the country whereas the riparian forests occupy western and eastern Sierra Leone. Degraded forests are found in the west of the country.

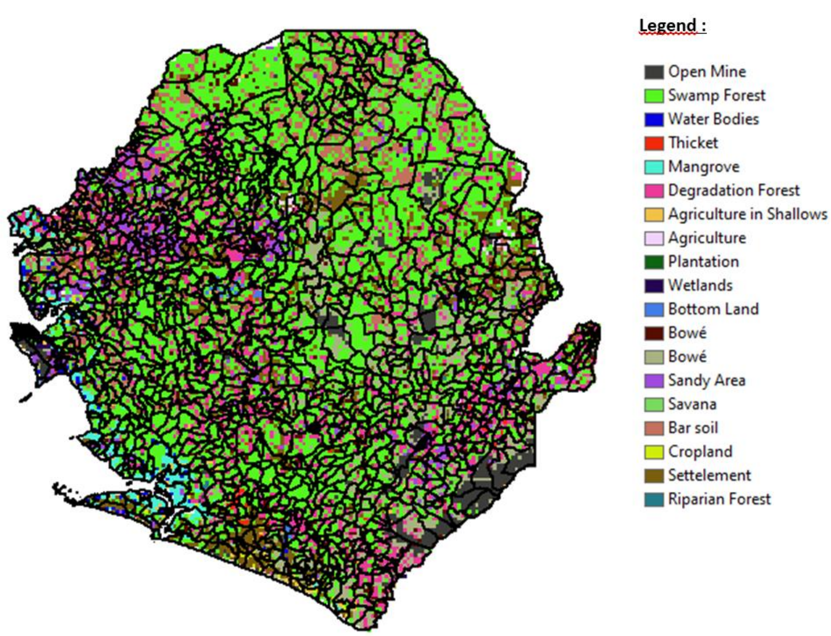

Figure 9. Land use land cover in Sierra Leone

Observed changes in land cover. To analyze the landslide hazard, an assessment of the mean changes of LULC was first conducted. Most districts (reddish districts in Fig. 10.a) have a positive change (i.e., increased likelihood of the landslide hazard). Bonthe has the highest change (23.7%), closely followed by the Pujehun (23.4%). A few districts however depict a negative change (blueish districts in Fig 10.a), including Port Loko (-22.9%), Tonkolili (-11.1%), Kono (-8.1%), the Western Area Rural district (-4.4%) and Bombali (-1.5%).

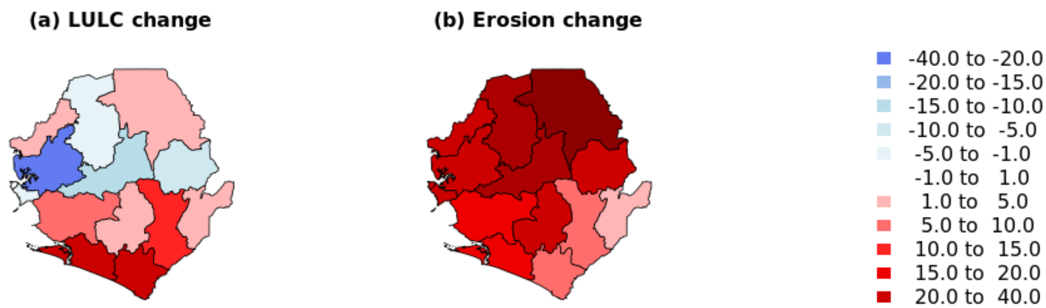

Figure 10. Changes in (a) LULC and (b) erosion (in % of district area). Positive values mean higher likelihood of the landslide hazard.

Erosion-prone areas. The erosion change is relatively marked in northern Sierra Leone (Koinadugu, Tonkolili, Bombali districts), while the southern districts (e.g., Pujehun) experience a lower erosion (Fig 10.b). Therefore, there is a mismatch between the areas with the fastest change in LULC and those of large erosion (Fig. 10.a vs 10.b).

b. Flood and Landslide exposure

The hazard exposure (Fig. 11 for floods and Fig 15.a for landslide exposure) is obtained here by combining the hazard information with the population estimate, both aggregated at the district level. Normalization of the ultimate exposure indicator is done to allow the comparison.

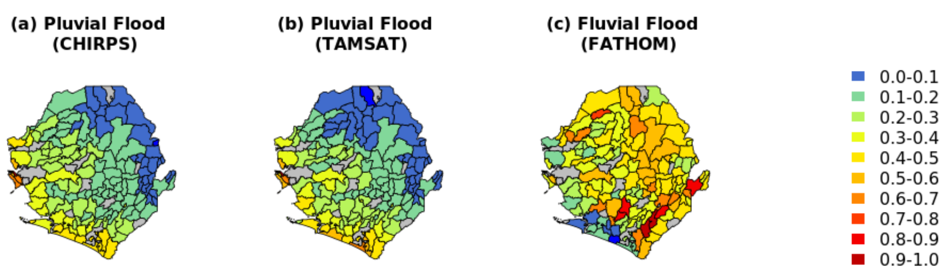

Figure 11. Chiefdom-level pluvial flood exposure maps using (a) CHIRPS and (b) TAMSAT and (c) fluvial flood exposure map using FATHOM. Grey-colored chiefdoms represent locations with no data. All scores are normalized with 1 (0) meaning highest (lowest) exposure.

In terms of exposure to pluvial flooding, both CHIRPS (Fig. 11.a) and TAMSAT (Fig. 11.b) consistently point to the western and southern chiefdoms as being the most exposed. Singularly, chiefdoms located in the Western Area Urban and Western Area Rural districts come out as the most exposed, driven by the high values of RL5 and the important density of settlements. Thus, the EAST III ward of Freetown ranks as the most exposed to floods in Sierra Leone (mostly because of its density and exposure to heavy rains), followed by the Waterloo Rural chiefdom (in the Western Area Rural district). The chiefdoms located in the south of the country, more precisely in the Bonthe and Pujehun districts, also have high exposure to pluvial floods. The least exposed areas are found in the north and east of the country (bluish chiefdoms on Fig.11), remarkably consistent across the two datasets. They are mostly found in the Koinadugu and Kono districts as well as parts of Bombali.

When it comes to fluvial flooding (Fig. 11.c), the southeastern chiefdoms are the most exposed, marking a clear contrast with pluvial flooding. This includes chiefdoms located in Chiefdoms located in the Kenema, Bo, Kailahun, Pujehun, Port Loko and Koinadugu (which is the least exposed to pluvial floods). The top five exposed chiefdoms are Koya (Kenema district), Barri (Pujuhun district), Lugbu (Bo district), Dama (Kenema district) and Luawa (Kailahun district), all located near the Sewa and Moa rivers. A few chiefdoms located along the Little Scarcies river also have high exposure to fluvial flooding. They include Sella Limba (Bombali district), Sanda Magbolontor (Port Loko distruct) and Masungbala (Kambia district). Given the absence of a critical water body, the Western Area Urban district (which is the most exposed to pluvial floods) has no exposure to fluvial floods. Therefore, the overall configuration is that there is a limited juxtaposition of pluvial and fluvial flood exposure.

Regarding landslides (Fig. 15.a), the most exposed districts are the Western Area Urban district and Pujehun, driven mostly by both the intensity of extreme rainfall the large LULC degradation. The least exposed areas are the eastern districts of Kailahun and Kono.

c. Vulnerability profile

Households in Sierra Leone are highly vulnerable to the impacts of floods and landslides, owing to high reliance on climate-sensitive activities, relatively high poverty levels, poor infrastructure, limited access to critical services like healthcare – especially in rural areas, and high population densities in at-risk areas. For this analysis and based on consultations with the World Bank, we compare two approaches to define vulnerability: the first approach considers composite vulnerability index based on a variety of indicators and the second approach is based on World Bank estimates of poverty at the chiefdom level (Fig. 12).

The composite vulnerability index (derived from socioeconomic indicators from the Census, Table 2) shows relatively high vulnerability levels outside of Freetown: mainly in chiefdoms located in Kailahun, followed by Kenema, Kono, Tonkolili and Bombali (Fig. 12.a). Poverty in Sierra Leone has strong spatial variability: 60 percent of the rural population lives in poverty compared 20 percent in urban areas (2015). Relative poverty is highest in the North region and lowest in the West and South. That said, the highest number of poor people (in absolute terms) live in the slums of Greater Freetown. The poverty index shows higher vulnerabilities in eastern parts of the country (Kenema City, Neya, Nieni) (Fig. 12.b). In part, this is driven by the high population numbers in the western and central districts of the country. The striking difference in vulnerability distribution according to the composite vulnerability index is due to the contribution of factors such as proportion of female-headed households, proportion of agricultural households and proportion of people with disabilities – this suggests that the composite vulnerability index is picking up additional vulnerabilities beyond income poverty. A granular analysis focused on the Western Urban and Rural district is presented in Annex 5.

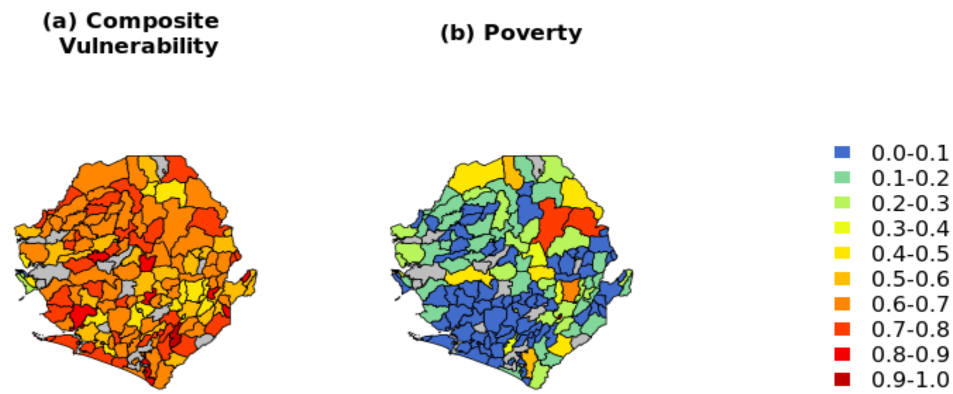

Figure 12. Chiefdom-level (a) composite vulnerability indicator (CVI) and (b) poverty maps. Grey-colored chiefdoms represent locations with no data. All scores are normalized with 1 (0) meaning highest (lowest) vulnerability.

4. Overall risk profile

a. Pluvial flood risk

Four maps of pluvial risk are generated using the two hazard datasets (CHIRPS and TAMSAT) and two vulnerability definitions (CVI and poverty). The results are sensitive to the vulnerability indicator.

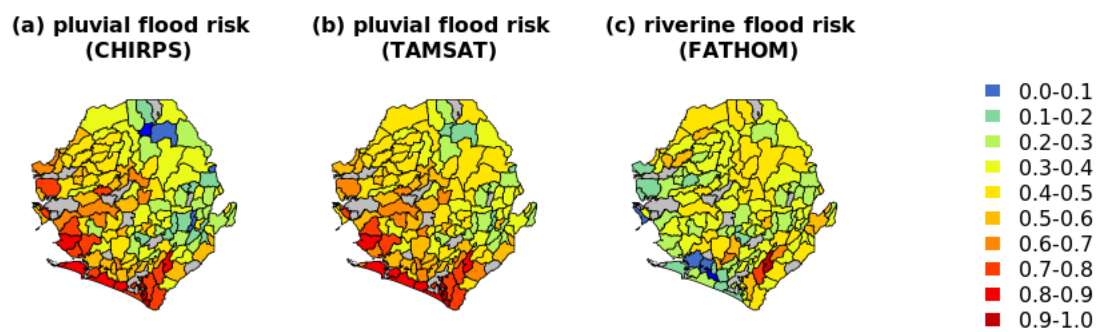

Figure 13. Chiefdom-level risk maps based on CVI: (a) pluvial flood risk using CHIRPS, (b) pluvial flood risk using TAMSAT, (c) fluvial flood risk using FATHOM. Grey-colored chiefdoms represent locations with no data. All scores are normalized with 1 (0) meaning highest (lowest) risk.

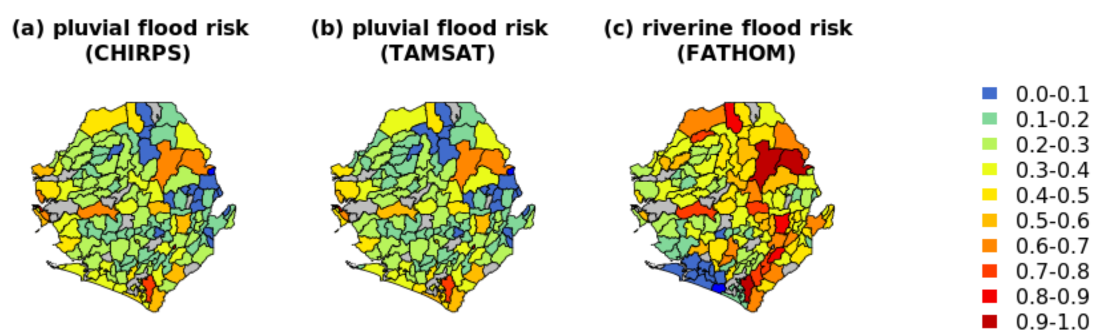

Figure 14. Chiefdom-level risk maps based on poverty: (a) pluvial flood risk using CHIRPS, (b) pluvial flood risk using TAMSAT, (c) fluvial flood risk using FATHOM. Grey-colored chiefdoms represent locations with no data. All scores are normalized with 1 (0) meaning highest (lowest) risk.

Using the composite vulnerability (Fig. 13.a & 13.b and Table 3), the most-at-risk chiefdoms are in the south of the country mostly driven by the exposure to intense rainfall. This is the result of the mismatch between the exposure and CVI vulnerability, as the latter has moderate values in the western chiefdoms. Thus, the top-at-risk districts in Sierra Leone based on CHIRPS include Kpaka (Pujehun district), Koya (Kenema district), Nongaba Bullom (Kenema district), Kagboro (Moyamba district) and Dema (Bonthe district). The ranking of the districts is consistent across CHIRPS and TAMSAT. The chiefdoms of the Koinadugu (e.g., Wara Wara Yagala and Sengbe) and Kono districts (e.g., Toni) districts in the northeast of the country are consistently ranked as the least at-risk.

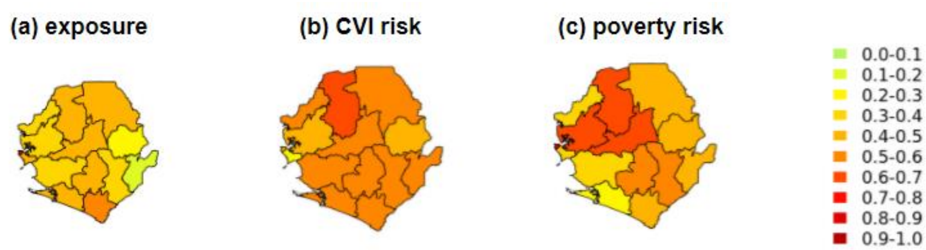

Figure 15. Landslide metrics using WFP/FAO data: (a) exposure, (b) risk based on CVI as vulnerability indicator, (c) risk based on poverty as vulnerability indicator. All scores are normalized with 1 (0) meaning highest (lowest) exposure or risk.

The profiles change significantly when poverty is used (Fig. 14.a & 14.b and Table 3) as vulnerability indicator. The most at-risk chiefdoms are found in the Western Area Urban district (East III ward being the riskiest area in the country) and Koinadugu. The high-risk profiles in these two districts are driven by two distinct factors. For the Western Area Urban district, the high exposure is the main driver. The East End of Freetown for example hosts the city's largest population center and receives important precipitation. Koinadugu, in the north of the country, has substantial vulnerability. The other end of the risk table is made of chiefdoms located in the Kono district as well as at the boundary between Bombali and Koinadugu.

Table 3.Risk scores using the (blue shades) poverty and (grey shades) CVI vulnerability indicators for the top 10 ranked chiefdoms of each instance

Poverty						**CVI**					
Pluvial flood (CHIRPS)		Pluvial flood (TAMSAT)		Pluvial flood (FATHOM)		Pluvial flood (CHIRPS)		Pluvial flood (TAMSAT)		Pluvial flood (FATHOM)	
Chiefdom	Score	Chiefdom	Score	Chiefdom	Score	Chiefdom	Score	Chiefdom	Score	Chiefdom	Score
East III	1	Kenema Town	1	Nieni	1	Kpaka	1	Kpaka	1	Koya	1
Kenema Town	0.99	East III	0.96	Galliness Perri	0.91	Koya	0.88	Sittia	0.89	Barri	0.79
Galliness Perri	0.72	Galliness Perri	0.74	Neya	0.9	Nongoba Bullom	0.86	Nongoba Bullom	0.88	Lugbu	0.65
Nieni	0.67	Nieni	0.66	Lower Bambara	0.82	Kagboro	0.86	Mono Sakrim	0.86	Dama	0.62

Waterloo Rural	0.67	Waterloo Rural	0.62	Wara Wara Bafod	0.82	Sittia	0.85	Koya	0.85	Luawa	0.59
Neya	0.63	Neya	0.61	Dama	0.81	Dema	0.85	Kagboro	0.83	Kpanda Kemo	0.58
Yoni	0.61	Yoni	0.59	Gorama Mende	0.8	Kwamebai Krim	0.81	Kwamebai Krim	0.82	Galliness Perri	0.56
Kaffu Bullom	0.61	Lower Bambara	0.58	Barri	0.78	Mono Sakrim	0.79	Bendu-Cha	0.82	Sella Limba	0.55
Lower Bambara	0.59	Kaffu Bullom	0.57	Koya	0.75	Waterloo Rural	0.79	Galliness Perri	0.78	Masungba la	0.54
York Rural	0.57	Tunkia	0.54	Sella Limba	0.74	Bendu-Cha	0.78	Soro Gbema	0.78	Kissi Kama	0.53

A cross comparison of risk levels according to indices derived from composite vulnerability and multidimensional poverty therefore shows strong inconsistencies. This calls for a careful examination of the rationale behind selecting vulnerability metrics, whether they are solely based on poverty or a composite index considering several factors. Our recommendation is to use the poverty-based risk analysis because poverty rates are already currently used for decision-making, and because poverty estimates are updated on a more regular basis. The composite vulnerability analysis is available as an additional layer to inform decision-making.

b. Fluvial flood risk

As with pluvial flooding, fluvial flooding risk is also strongly dependent on the choice of the vulnerability indicator. Using the composite vulnerability index (Fig. 13.c and Table 3), the southern chiefdoms are the most at-risk districts owing to a good match between CVI and the FATHOM flood exposure for the upper parts of their respective tables. Thus, Koya, Barri, Lugba, Dama and Luawa are the riskiest districts. At the bottom of the risk table, not considering the Western Area chiefdoms where there are no large water bodies to cause fluvial flooding, the chiefdoms in Bonthe make up the list of low flood risk. A moderately different ranking is obtained when poverty is used as the vulnerability indicator (Fig. 14.c and Table 3). Here, in addition to the southeastern chiefdoms listed above, the chiefdoms of Nieni and Neya in the Koinadugu district have some of the highest risks. If for the southeastern chiefdoms, the risk is driven by the high exposure created by the crossing of the Sewa and Moi rivers, in Nieni and Koinadugu, it is mostly the high poverty rates that is the main explaining factor. And this same factor also justifies the closer profiles of pluvial and fluvial flood risk when poverty is solely used as the vulnerability measure.

c. Landslide risk

Landslide risk is also a function of the vulnerability indicator. From a CVI perspective (Fig. 15.b and Table 3), the risk is similar throughout the country with the riskiest district (Bombali) scoring 0.60 versus 0.27 for the least at-risk district (Western Area Rural district). In addition, nine districts have a score between 0.5 and 0.6, highlighting the minor difference across them.

As for the risk calculated using poverty-based vulnerability (Fig. 14.d and Table 1), it is more marked across the district. The preeminence of the Western Area Urban district is well marked as it scores 0.87, above the second riskiest district of Bombali (0.68). The least at-risk district is Bonthe here, scoring 0.25 (which is lower than the smallest score using CVI).

d. Relationship between risk indices and SSN beneficiary coverage

The risk layers have weak correlations with NACSA's current and planned Social Safety Net program coverage (Figure 16). Overall, for the cumulative number of beneficiary households in 2014-2020, the risk indices have poor correlations. Correlations are slightly better for the coverage in 2020, but overall correlations are lower in the 2022 scale-up. While households were selected for the 2022 scale-up according to poverty rates, other criteria were included – which explains the low correlations.
Correlations are even weaker between risk calculations based on the composite vulnerability index and SSN coverage (Figure 17).

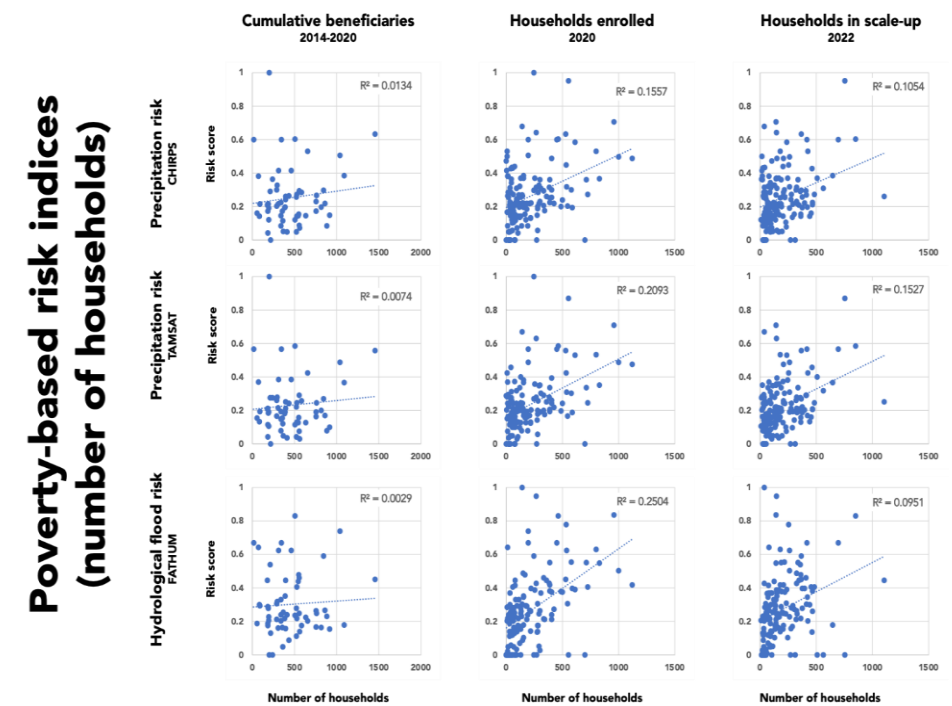

Figure 16. Correlation between number of households enrolled in the SSN program cumulatively between 2014 and 2020 (left), in 2020 and receiving a payment until 2021 (center), and in the scale-up for 2022 (right) and poverty-based risk indices based on CHIRPS flood risk (top), TAMSAT flood risk (middle) and FATHUM fluvial risk (bottom).

In some instances, there is no discernible correlation (for instance, the R^2 value between household enrolment in the 2022 scale-up and the CHIRPS-based flood risk is 0). (Additional analysis using household proportions is presented in Annex 4).

This illustrates the fact that climate risk factors are not yet embedded in decisions for scale-up and that there is significant potential to incorporate flood risk information into future SSN programs. Moving forward, we recommend the use of these risk layers to identify chiefdoms at high risk of flood and landslide risks to prepare for scaling up SSN programs in the event of a disaster.

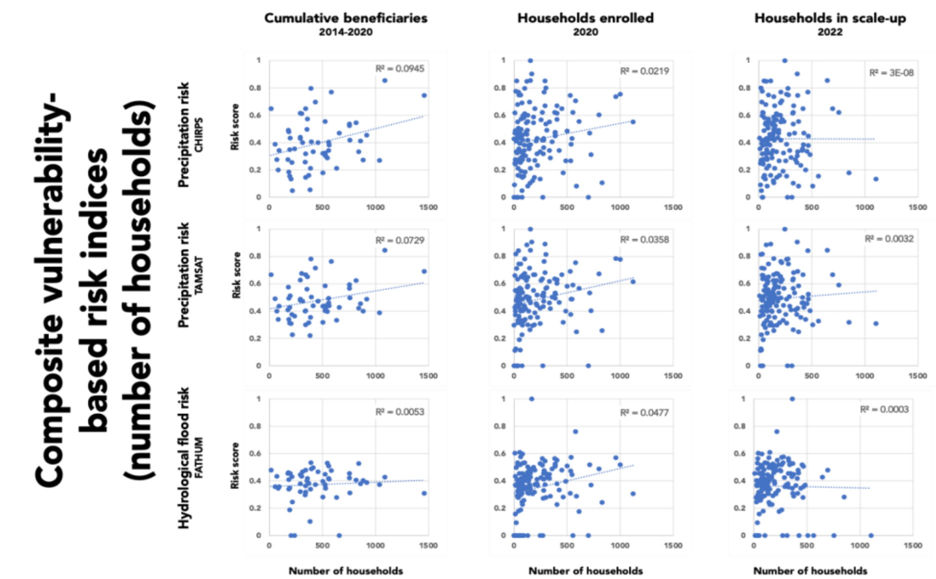

Figure 17. Correlation between number of households enrolled in the SSN program cumulatively between 2014 and 2020 (left), in 2020 and receiving a payment until 2021 (center), and in the scale-up for 2022 (right) and composite vulnerability-based risk indices based on CHIRPS flood risk (top), TAMSAT flood risk (middle) and FATHUM fluvial risk (bottom).

5. Summary and Recommendaiton

A comprehensive risk and vulnerability analysis was developed for Sierra Leone. The objective of the analysis is to quantitatively and spatially identify chiefdoms that are highly exposed to flood and landslide risks. The result of the analysis is instrumental for the operation and monitoring of a shock-responsive social protection system. It informs prioritization and targeting of social protection programs in the event of a shock. The analysis also provides the building block for conducting the activities in subsequent themes of the SRSP project, specifically in theme 3- *Institutionalizing preparedness measures within NACSA*, theme 5- *Defining 'triggers' for response*, and theme 6 - *Longer-term financial planning and links to safety nets*. The data inventory analysis performed under theme-I is the foundation for understanding the datasets that can be used for early warning systems and trigger mechanisms. It helps define what datasets might be used for market-based risk finance products and the extent to which these link to poverty. The risk analysis provides an overall picture of the risks and vulnerabilities that NASCA programs will need to respond to, including the frequency, scale, and type of shocks. It provides the basis for the development of the contingency planning scenario and for developing targeting strategies in NACSA contingency planning operational manual. The trigger design will directly build on the risk analysis to define the parameters and the most appropriate disaster risk financing instrument. By linking these themes, we will maximize the synergies between effective contingency planning process, and the potential to integrate data-driven triggers for shock responsive social protection.

The risk and vulnerability analysis followed the definitions in disaster management and climate change adaptation framework. Risk is defined as the probability of occurrence of hazardous events or trends multiplied by the impacts if these events or trends do take place. Following this framework, risk is calculated through a combination of hazard, exposure, and vulnerability. Hazard is measured by rainfall intensity and landslide frequency, while exposure is defined as the number of people living in a hazardous area. Two definitions of vulnerability are provided: a vulnerability indicator based on Poverty (MDPI) and Composite Vulnerability Index (CVI) based on multiple indicators (including poverty, the proportion of female-headed households, proportion of agricultural households, and proportion of people with disabilities among others). Adaptation measures, such as nature-based solutions, asset creation, and improving access to insurance can help reduce vulnerability – but an assessment of these activities is outside the scope of the current analysis.

The analysis illustrates that pluvial flood hazards (i.e., floods resulting from heavy precipitation) are concentrated in the western and southern parts of the country, whereas riverine flood (flood associated with rivers exceeding their capacity) risk occurs throughout the country. The choice of vulnerability indicators also matters. Results indicate that pluvial flood risk is highest in the Western Area Urban district when poverty-based vulnerability index is applied (East III ward being the riskiest area in the country), whereas the chiefdoms in the south of the country are the most at risk when other dimensions of vulnerability, such as the proportion of female headed households, proportion of agricultural households, proportion of people with disabilities, among others are considered in addition to poverty. Careful examination of the rationale behind selecting vulnerability metrics is necessary as the high-risk areas identified depend on the vulnerability indicator considered. Our recommendation is to use poverty-based risk analysis because poverty rates are already currently used for decision-making, and because poverty estimates are updated on a more regular basis. The composite vulnerability analysis is available as an additional layer to inform decision-making. The results also illustrate that the high-risk areas have weak correlation with NACSA's current and planned Social Safety Net program coverage. This is to be expected as beneficiaries to social protection programs may not necessarily be selected based on climate risk. Moving forward, we recommend that NACSA expand their registry in chiefdoms at high-risk of flooding and landslides to quickly scale up the SSN and other social protection programs in the event of a disaster.

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Annex 1. Correlation matrix of indicators from 2015 Census

Table A1 1. Correlation matrix of all indicators selected for analysis. Indicators were removed if they were highly autocorrelated to others to prevent distortion in the final results.

Correlation Matrix[a]

		crop	animal_husbandry	fisheries	upland_rice	lowland_rice	cassava	maize	disabilities	illiteracy	deprived_healthcare	unemployed	elderly	female_hh	roof_thatch	roof_tarp	wood_floor	mud_floor	total_pop_perc	age_depend	poverty_rate	mdpi	poor_water	poor_floor
Correlation	crop	1.000	0.925	0.843	0.859	0.778	0.449	0.539	0.643	0.857	0.351	-0.946	-0.406	0.321	0.620	-0.269	0.002	0.672	-0.632	0.889	0.863	0.885	0.724	0.977
	animal_husbandry	0.925	1.000	0.755	0.698	0.812	0.471	0.551	0.563	0.790	0.521	-0.890	-0.491	0.435	0.501	-0.148	-0.105	0.526	-0.717	0.923	0.882	0.876	0.810	0.890
	fisheries	0.843	0.755	1.000	0.720	0.444	0.619	0.511	0.589	0.700	0.334	-0.763	-0.581	0.203	0.730	-0.443	-0.182	0.362	-0.676	0.669	0.701	0.743	0.631	0.810
	upland_rice	0.859	0.698	0.720	1.000	0.557	0.109	0.608	0.638	0.632	0.237	-0.813	-0.120	0.337	0.582	-0.099	0.255	0.816	-0.301	0.660	0.593	0.631	0.419	0.798
	lowland_rice	0.778	0.812	0.444	0.557	1.000	0.120	0.350	0.157	0.624	0.476	-0.746	-0.348	0.264	0.183	0.022	0.133	0.440	-0.446	0.766	0.707	0.714	0.703	0.747
	cassava	0.449	0.471	0.619	0.109	0.120	1.000	0.093	0.423	0.621	0.047	-0.325	-0.520	0.052	0.554	-0.636	-0.356	0.022	-0.662	0.484	0.601	0.633	0.583	0.533
	maize	0.539	0.551	0.511	0.608	0.350	0.093	1.000	0.376	0.469	0.637	-0.555	-0.210	0.183	0.488	-0.066	0.170	0.499	-0.350	0.593	0.560	0.578	0.612	0.535
	disabilities	0.643	0.563	0.589	0.638	0.157	0.423	0.376	1.000	0.556	-0.041	-0.664	0.026	0.250	0.455	-0.345	-0.200	0.672	-0.378	0.528	0.503	0.490	0.234	0.626
	illiteracy	0.857	0.790	0.700	0.632	0.624	0.621	0.469	0.556	1.000	0.376	-0.846	-0.329	0.307	0.768	-0.292	0.070	0.653	-0.636	0.904	0.953	0.938	0.752	0.922
	deprived_healthcare	0.351	0.521	0.334	0.237	0.476	0.047	0.637	-0.041	0.376	1.000	-0.444	-0.226	0.447	0.303	0.172	0.226	0.172	-0.295	0.541	0.528	0.478	0.571	0.321
	unemployed	-0.946	-0.890	-0.763	-0.813	-0.746	-0.325	-0.555	-0.664	-0.846	-0.444	1.000	0.280	-0.346	-0.588	0.156	-0.033	-0.719	0.556	-0.859	-0.835	-0.806	-0.641	-0.908
	elderly	-0.406	-0.491	-0.581	-0.120	-0.348	-0.520	-0.210	0.026	-0.329	-0.226	0.280	1.000	0.176	-0.297	0.158	0.614	0.263	0.856	-0.391	-0.467	-0.466	-0.557	-0.418
	female_hh	0.321	0.435	0.203	0.337	0.264	0.052	0.183	0.250	0.307	0.447	-0.346	0.176	1.000	0.395	0.268	0.348	0.332	-0.036	0.486	0.345	0.353	0.283	0.287
	roof_thatch	0.620	0.501	0.730	0.582	0.183	0.554	0.488	0.455	0.768	0.303	-0.588	-0.297	0.395	1.000	-0.213	0.127	0.439	-0.479	0.635	0.685	0.710	0.557	0.677
	roof_tarp	-0.269	-0.148	-0.443	-0.099	0.022	-0.636	-0.066	-0.345	-0.292	0.172	0.156	0.158	0.268	-0.213	1.000	0.173	0.001	0.206	-0.142	-0.221	-0.312	-0.285	-0.307
	wood_floor	0.002	-0.105	-0.182	0.255	0.133	-0.356	0.170	-0.200	0.070	0.226	-0.033	0.614	0.348	0.127	0.173	1.000	0.406	0.639	0.006	-0.055	0.007	0.007	-0.009
	mud_floor	0.672	0.526	0.362	0.816	0.440	0.022	0.499	0.672	0.653	0.172	-0.719	0.263	0.332	0.439	0.001	0.406	1.000	-0.097	0.612	0.564	0.539	0.244	0.669
	total_pop_perc	-0.632	-0.717	-0.676	-0.301	-0.446	-0.662	-0.350	-0.378	-0.636	-0.295	0.556	0.856	-0.036	-0.479	0.206	0.639	-0.097	1.000	-0.701	-0.765	-0.723	-0.663	-0.676
	age_depend	0.889	0.923	0.669	0.660	0.766	0.484	0.593	0.528	0.904	0.541	-0.859	-0.391	0.486	0.635	-0.142	0.006	0.612	-0.701	1.000	0.971	0.963	0.842	0.923
	poverty_rate	0.863	0.882	0.701	0.593	0.707	0.601	0.560	0.503	0.953	0.528	-0.835	-0.467	0.345	0.685	-0.221	-0.055	0.564	-0.765	0.971	1.000	0.976	0.843	0.918
	mdpi	0.885	0.876	0.743	0.631	0.714	0.633	0.578	0.490	0.938	0.478	-0.806	-0.466	0.353	0.710	-0.312	0.007	0.539	-0.723	0.963	0.976	1.000	0.896	0.944
	poor_water	0.724	0.810	0.631	0.419	0.703	0.583	0.612	0.234	0.752	0.571	-0.641	-0.557	0.283	0.557	-0.285	0.007	0.244	-0.663	0.842	0.843	0.896	1.000	0.769
	poor_floor	0.977	0.890	0.810	0.798	0.747	0.533	0.535	0.626	0.922	0.321	-0.908	-0.418	0.287	0.677	-0.307	-0.009	0.669	-0.676	0.923	0.918	0.944	0.769	1.000

Annex 2. Principal component analysis

To enable comparison between indicators and to remove the effect of variability in the data, indicators were averaged at the district level and subsequently normalized with zero representing the average value of the indicator, and larger numbers in either direction indicating higher variance from the average:

$$z\ score = \frac{X_i - \mu}{\sigma} \qquad \text{(Eq. 1)}$$

Where Xi is the original value of the indicator, μ is the average value of the indicators, and σ is the standard deviation. This normalization method is utilized to facilitate interpretation of the variability that the data contain.

As a next step, pairwise correlation tests were carried out to reduce the initial set of metrics to non-highly correlated indicators ($R < 0.7$) – this resulted in the elimination of ten indicators from the analysis. Additionally, indicators that had low variance ($\boldsymbol{\sigma^2}$<0.3) explained by components were removed from the analysis.

The principal component analysis was conducted using SPSS 26. PCA uses orthogonal linear transformation to identify a vector in an N-dimensional space that accounts for as much of the total variability in a set of N variables as possible (the first principal component (PC)). A second vector (second PC), orthogonal to the first, is then sought, which accounts for as much of the remaining variability as possible in the original variables. Each succeeding PC is linearly uncorrelated to the others and accounts for as much of the remaining variability as possible (Jolliffe, 2002).

The PCA was performed by applying a promax rotation to allow components to be correlated – this reflects the reality of vulnerability indicators. The Kaiser-Mayer-Olkin (KMO) sampling adequacy test values were high (>0.8) and Bartlett's sphericity tests returned $p<0.05$ for all PCA analyses, suggesting that the variables were suitable for PCA analysis (Hair et al., 2006). Components were kept if the eigenvalue of the component was >1.0 (Griffith et al., 2000). The choice of PCs to be retained from the PCAs was in part based on subjective judgement and interpretability of the components (Srivastava, 2002). The specific aspects of vulnerability represented by each PC were defined by the loadings of each indicator on that component: for instance, if a principal component was heavily loaded on indicators of infrastructure quality, then the vulnerability scores resulting from that PC would be regarded as a summary of infrastructure quality. A total of four PCs describe characteristics of vulnerability, explaining 83.9% of the total variation in vulnerability (Table A2.1).

The indicators in each PC with high factor loadings (>0.4) can be functionally grouped to describe that component (see Annex 4 for an overview of the principal components, indicators, and associated loadings). The score of each principal component is estimated based on linear regression. Consequently, two sets of component scores were computed to determine flood and drought vulnerability, respectively. Overall vulnerability scores were calculated by adding the eigenvalue-weighted value of each PC score. The final scores were then normalized using the following formula:

$$X_{normal} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad \text{(Eq. 2)}$$

Where Xnormal is the normalized value, Xi is the original value, Xmax and Xmin are the maximum and minimum score values. The final vulnerability scores range from 0 to 1, with a higher score indicating higher vulnerability levels. This normalization process provides an objective ranking of districts according to vulnerability levels. For visualization purposes, values were then divided into equal quintiles, with each quintile representing a vulnerability category (0.0-0.2: very low; 0.2-0.4: low, 0.4-0.6: medium, 0.6-0.8: high; 0.8-1.0: very high).

BOX 1: Principal component analysis – what is it and how to interpret results?

Principal component analysis is a technique that combines various input variables so that the least important variables are dropped while keeping the most significant variables (i.e., those with high variability). The technique also ensures that the retained variables are independent of each other, avoiding problems of autocorrelation between variables.

To reduce complexity in the datasets, a PCA identifies directions, called principal components, along which the direction of data is maximal. The process then groups variables based on how well they explain an outcome (e.g., vulnerability) in combination.

Each principal component is associated with an eigenvalue, which indicates how significant the PC is (an eigenvalue indicates the amount of variability contained within a data sample; a larger value suggests higher explanatory power). The first PC explains more variability in the outcome of interest. The eigenvalue provides a statistically based approach to provide weights to indicators. In this analysis we weighted principal components based on the eigenvalue associated with it.

How many principal components are retained is ultimately a subjective exercise? Each PC is associated with a proportion of variance that explains the outcome. As more PCs are retained, the analysis explains the outcome more accurately. For this exercise we retained four PCs for the vulnerability index, explaining at least 80% of variation in vulnerability, without providing too much complexity and noise to the analysis.

Table A2 1. Results of Principal Component Analysis. Loading factors with a value >0.4 are highlighted for reference.

Variable	Principal Component			
	PC1	**PC2**	**PC3**	**PC4**
Poor floors	0.971	0.018	-0.119	-0.093
MDPI (multidimensional poverty index)	0.965	-0.055	0.068	0.137
Age dependency	0.958	0.078	0.140	0.003
Households engaged in cropping	0.958	0.074	-0.107	-0.185
Households engaged in animal husbandry	0.938	0.001	0.146	-0.177
Adult illiteracy	0.925	0.023	-0.102	0.142
Unemployed population	-0.914	-0.190	0.078	0.219
Households engaged in fisheries	0.839	-0.221	-0.179	0.037
Poor access to water	0.835	-0.156	0.332	0.225
Poor roofs	0.721	0.020	-0.176	0.438
Women headed households	0.374	0.488	0.193	0.285
Households deprived of healthcare	0.489	0.234	0.654	0.230
Population with disabilities	0.612	0.070	-0.636	-0.161
Eigenvalue	**12.9**	**3.16**	**1.99**	**1.25**
Cumulative variance explained (%)	**56.07**	**69.8**	**78.46**	**83.89**

Annex 3. Flood and landslide exposure and risk profiles at district level

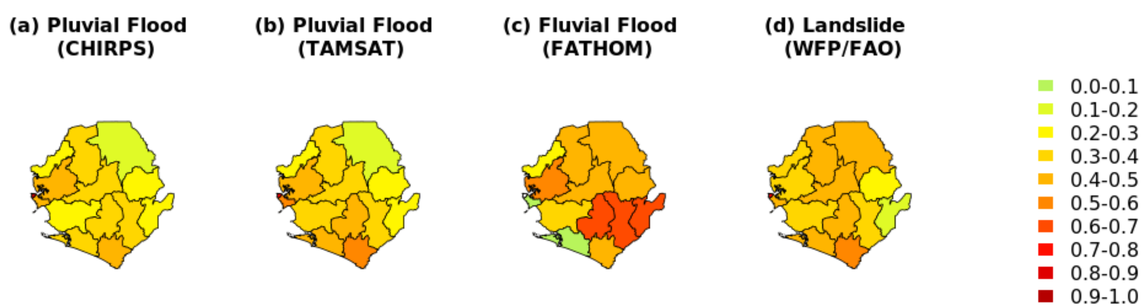

Figure A3 1. Figure A3.1. District-level pluvial flood exposure maps using (a) CHIRPS and (b) TAMSAT, (c) fluvial flood exposure map using FATHOM and (d) landslide exposure map using WFP and FAO.

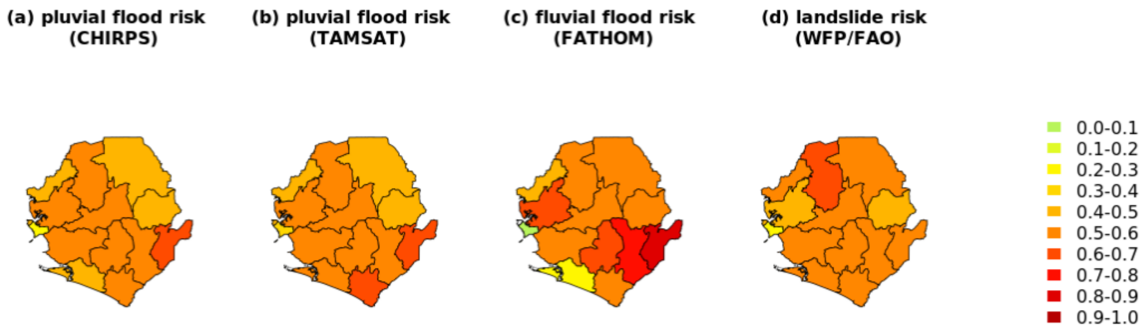

Figure A3 2. District-level risk maps based on CVI: (a) pluvial flood risk using CHIRPS, (b) pluvial flood risk using TAMSAT, (c) fluvial flood risk using FATHOM, (d) landslide risk map using WFP and FAO.

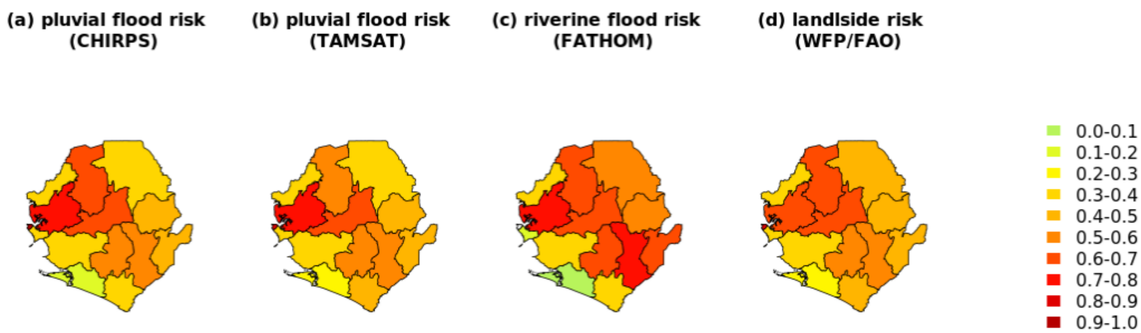

Figure A3 3. Same as Figure A3.2 based on poverty.

Table A3 1. District-level risk scores using the (blue shades) CVI and (grey shades) poverty-based vulnerability indicators

	Composite Vulnerability				**Multidimensional Poverty**			
District	**Pluvial (CHIRPS)**	**Pluvial (TAMSAT)**	**Fluvial (FATHOM)**	**Landslide (WFP/FAO)**	**Pluvial (CHIRPS)**	**Pluvial (TAMSAT)**	**Fluvial (FATHOM)**	**Landslide (WFP/FAO)**
Kailahun	0.62	0.63	0.80	0.60	0.43	0.44	0.61	0.40
Kenema	0.54	0.57	0.73	0.57	0.54	0.57	0.73	0.57
Kono	0.47	0.48	0.60	0.48	0.44	0.45	0.57	0.45
Bombali	0.52	0.52	0.60	0.60	0.60	0.60	0.68	0.68
Kambia	0.48	0.47	0.48	0.52	0.32	0.31	0.33	0.36
Koinadugu	0.40	0.40	0.58	0.56	0.33	0.33	0.50	0.49
Port Loko	0.57	0.57	0.62	0.50	0.73	0.73	0.77	0.65
Tonkolili	0.53	0.55	0.56	0.58	0.60	0.62	0.64	0.65
Bo	0.51	0.54	0.64	0.53	0.53	0.56	0.66	0.55
Bonthe	0.44	0.51	0.27	0.51	0.17	0.25	0.01	0.25
Moyamba	0.53	0.57	0.56	0.56	0.31	0.34	0.33	0.34
Pujehun	0.54	0.62	0.54	0.59	0.38	0.45	0.38	0.42
WA Rural	0.29	0.32	0.09	0.27	0.33	0.36	0.13	0.31
WA Urban	0.50	0.41	0.00	0.42	0.95	0.86	0.00	0.87

Annex 4. Correlation between risk and SSN programme coverage

The risk layers and SNN coverage correlation results are very similar (with even poorer correlations) when considering the proportion of households (as opposed to the number of households) enrolled in the SSN program (Figure A4.1).

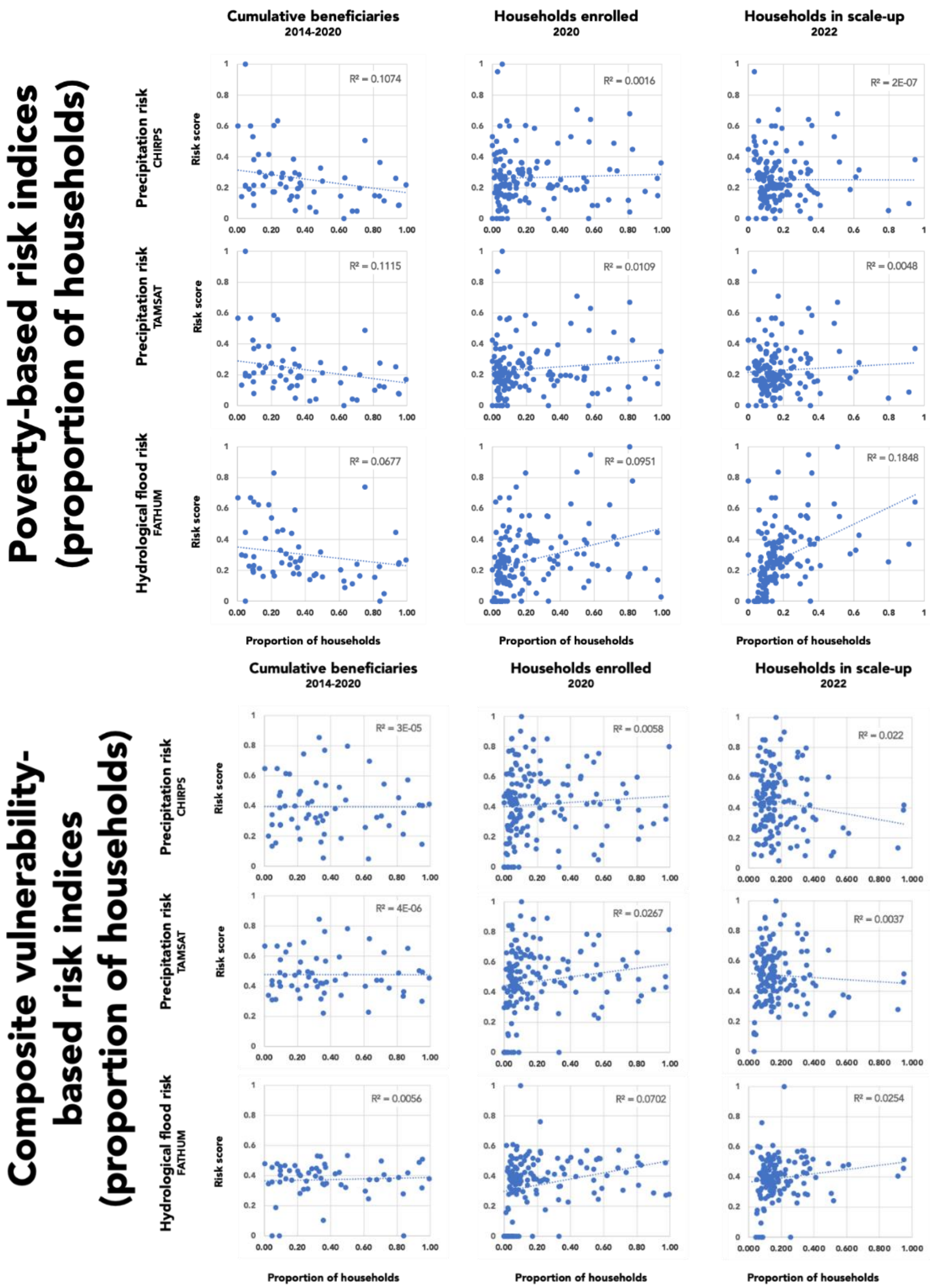

Figure A4 1. Correlation between proportion of households enrolled in the SSN program cumulatively between 2014 and 2020 (left), in 2020 and receiving a payment until 2021 (center), and in the scale-up for 2022 (right) and different risk indices based on CHIRPS flood risk (top), TAMSAT flood risk (middle) and FATHUM fluvial risk (bottom).

We also discern weak correlations between risk indices and the cumulative number of households enrolled in SSN program between 2014 and 2021 and including those enrolled in the SSN scale-up for 2022 (Figure A4.4).

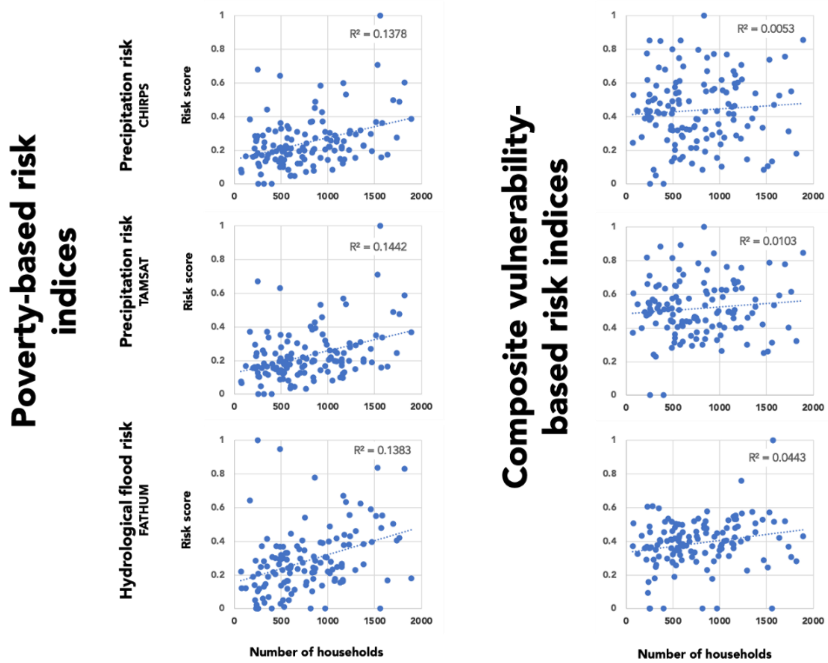

Figure A4 2. Correlation between proportion of households enrolled in the SSN program cumulatively between 2014 and 2022, and the poverty-based risk indices (left) and composite vulnerability-based indices (right).

Finally, we identify a very weak correlation (R^2=0.0006) between poverty rates and composite vulnerability scores (Figure A4.5). Although poverty rates are considered in the vulnerability analysis, there are indicators such as engagement in agriculture (lowland rice, upland rice, cassava, livestock rearing) and fisheries, age-dependency ratios, single female-headed households that do not closely match poverty rates. Despite the differences between vulnerability scores and poverty rates, both layers can provide useful inputs for decision-making.

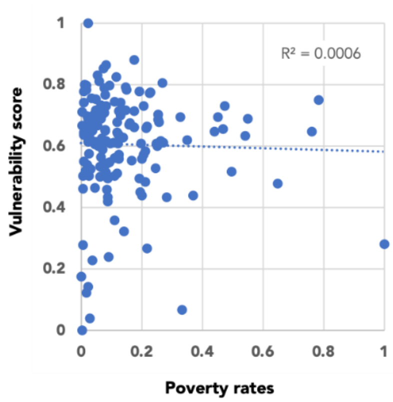

Figure A4 3. Correlation between vulnerability scores and poverty rates.

Annex 5. Flood risk analysis zoomed in the Western Area Urban and Rural districts

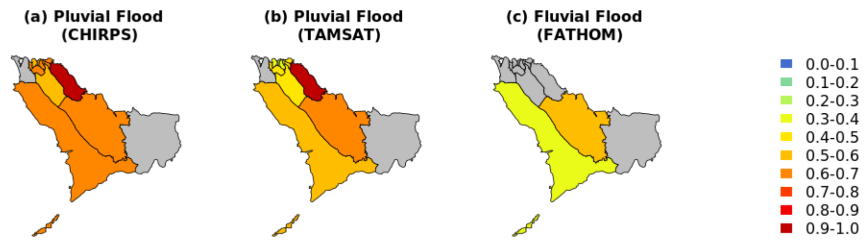

Figure A5.1. Chiefdom-level pluvial flood exposure maps using (a) CHIRPS and (b) TAMSAT and (c) fluvial flood exposure map using FATHOM for the Urban Area Urban and Rural districts. Grey-colored chiefdoms represent locations with no data. All scores are normalized with 1 (0) meaning highest (lowest) exposure.

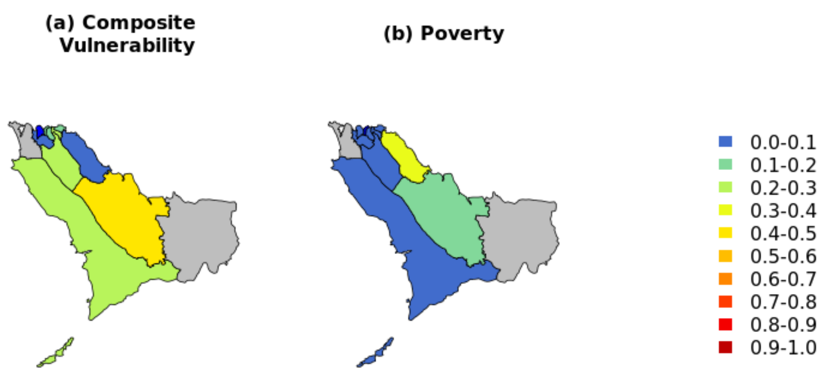

Figure A5.2. Chiefdom-level (a) composite vulnerability indicator (CVI) and (b) poverty maps for the Western Area Urban and Rural districts. Grey-colored chiefdoms represent locations with no data. All scores are normalized with 1 (0) meaning highest (lowest) vulnerability.

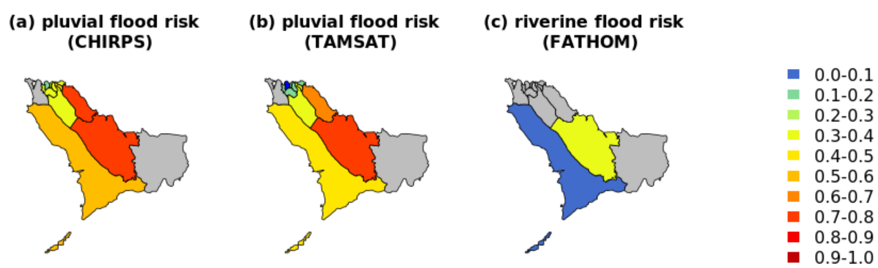

Figure A5.3. Chiefdom-level risk maps based on CVI: (a) pluvial flood risk using CHIRPS, (b) pluvial flood risk using TAMSAT, (c) fluvial flood risk using FATHOM for the Western Area Urban and Rural districts. Grey-colored chiefdoms represent locations with no data. All scores are normalized with 1 (0) meaning highest (lowest) risk.

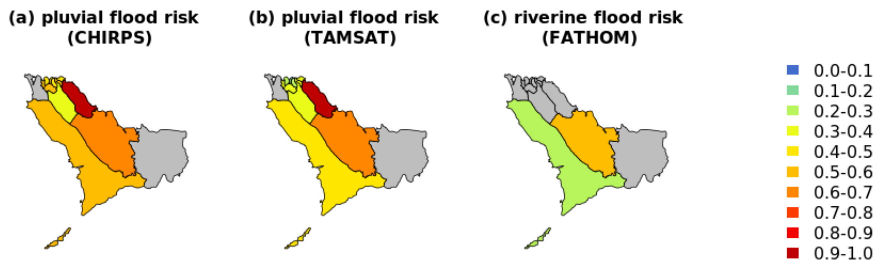

Figure A5.4. Chiefdom-level risk maps based on poverty: (a) pluvial flood risk using CHIRPS, (b) pluvial flood risk using TAMSAT, (c) fluvial flood risk using FATHOM for the Western Area Urban and Rural districts. Grey-colored chiefdoms represent locations with no data. All scores are normalized with 1 (0) meaning highest (lowest) risk.

Annex 6 Full Risk scores using the (blue shades) poverty and (grey shades) CVI vulnerability indicators

		Poverty			CVI		
Name	**Code**	**Pluvial flood (CHIRPS)**	**Pluvial flood (TAMSAT)**	**Fluvial flood (FATHOM)**	**Pluvial flood (CHIRPS)**	**Pluvial flood (TAMSAT)**	**Fluvial flood (FATHOM)**
Yakemu Kpukumu	SL030412	NA	NA	NA	NA	NA	NA
Koya	SL020412	NA	NA	NA	NA	NA	NA
Bureh Kasseh Ma	SL020401	NA	NA	NA	NA	NA	NA
Panga Kabonde	SL030404	NA	NA	NA	NA	NA	NA
Galliness Perri	SL030402	0.72	0.74	0.91	0.75	0.78	0.56
Kpaka	SL030403	0.40	0.44	0.11	1.00	1.00	0.31
Bum	SL030202	0.27	0.28	0.04	0.59	0.63	0.13
Komboya	SL030109	0.14	0.14	0.38	0.32	0.39	0.39
Valunia	SL030114	0.23	0.24	0.36	0.35	0.43	0.30
Barri	SL030401	0.31	0.33	0.78	0.70	0.73	0.79
Buya Romende	SL020402	0.22	0.18	0.17	0.44	0.43	0.19
Bramaia	SL020201	0.23	0.17	0.37	0.53	0.49	0.42
Kpanda Kemo	SL030206	0.18	0.18	0.46	0.61	0.62	0.58
Kwamebai Krim	SL030207	0.39	0.40	0.00	0.81	0.82	0.12
Nongoba Bullom	SL030208	0.34	0.39	0.09	0.86	0.88	0.26
Sittia	SL030209	0.35	0.40	0.03	0.85	0.89	0.20
Makpele	SL030405	0.28	0.33	0.40	0.37	0.48	0.30
Malen	SL030406	0.50	0.50	0.40	0.56	0.60	0.21
Mono Sakrim	SL030407	0.45	0.52	0.13	0.79	0.86	0.16

Sowa	SL030411	0.22	0.22	0.29	0.55	0.58	0.37
Panga krim	SL030408	0.37	0.36	0.18	0.76	0.75	0.26
Penguia	SL010112	0.16	0.15	0.33	0.28	0.35	0.31
Pejeh(Futa peje	SL030409	0.21	0.23	0.23	0.43	0.50	0.25
Soro Gbema	SL030410	0.52	0.53	0.61	0.77	0.78	0.50
Bendu-Cha	SL030201	0.31	0.35	0.09	0.78	0.82	0.24
Sulima	SL020309	0.18	0.17	0.32	0.40	0.43	0.33
Dema	SL030203	0.31	0.19	NA	0.85	0.67	NA
Imperri	SL030204	0.29	0.29	0.03	0.50	0.54	0.06
Jong	SL030205	0.31	0.30	0.08	0.52	0.55	0.09
Sanda Loko	SL020110	0.21	0.17	0.36	0.42	0.42	0.36
Sogbeni	SL030210	0.22	0.21	0.02	0.54	0.55	0.13
Yawbeko	SL030211	0.28	0.26	0.00	0.43	0.47	0.00
Dasse	SL030303	0.13	0.12	0.33	0.43	0.47	0.41
Selenga	SL030112	0.16	0.16	0.17	0.32	0.39	0.18
Bagruwa	SL030301	0.26	0.24	0.20	0.78	0.74	0.39
Bonthe Urban	SL030291	NA	NA	NA	NA	NA	NA
Bumpeh	SL030302	0.30	0.29	0.22	0.77	0.73	0.35
Simbaru	SL010213	0.16	0.17	0.56	0.33	0.40	0.52
Fakunya	SL030304	0.23	0.25	0.23	0.61	0.65	0.34
Gaura	SL010203	0.22	0.22	0.33	0.38	0.44	0.30
Kagboro	SL030305	0.40	0.41	0.18	0.86	0.83	0.28
Luawa	SL010108	0.15	0.14	0.66	0.29	0.35	0.59
Kandu Leppiama	SL010205	0.16	0.16	0.30	0.15	0.25	0.20
Kowa	SL030310	0.12	0.14	0.07	0.56	0.60	0.27
Kaiyamba	SL030306	0.16	0.17	0.32	0.27	0.37	0.28
Lower Banta	SL030311	0.24	0.22	0.50	0.33	0.38	0.40
Kongbora	SL030308	0.14	0.13	0.20	0.47	0.49	0.31
Kamajei	SL030307	NA	NA	NA	NA	NA	NA
Langrama	SL010207	0.13	0.14	0.25	0.58	0.61	0.43
Bagbo	SL030102	0.17	0.19	0.18	0.43	0.51	0.25
Kori	SL030309	0.18	0.18	0.24	0.49	0.52	0.32
Dama	SL010201	0.32	0.32	0.81	0.39	0.45	0.62
Ribbi	SL030312	0.32	0.29	0.25	0.62	0.60	0.29
Boama	SL030104	NA	NA	NA	NA	NA	NA
Dodo	SL010202	0.37	0.35	0.59	0.11	0.21	0.24
Timdale	SL030313	0.28	0.28	0.13	0.70	0.70	0.26
Upper Banta	SL030314	NA	NA	NA	NA	NA	NA
Gorama Mende	SL010204	0.51	0.49	0.80	0.28	0.35	0.39
Koya	SL010206	0.17	0.18	0.75	0.88	0.85	1.00
Lower Bambara	SL010208	0.59	0.58	0.82	0.19	0.27	0.27
Malegohun	SL010209	0.19	0.19	0.47	0.08	0.19	0.28
Niawa	SL010210	0.19	0.21	0.29	0.58	0.62	0.40

Njaluahun	SL010111	0.22	0.22	0.63	0.11	0.21	0.40
Nomo	SL010211	NA	NA	NA	NA	NA	NA
Nongowa	SL010212	0.30	0.28	0.68	0.26	0.33	0.46
Small Bo	SL010214	0.31	0.31	0.40	0.48	0.53	0.34
Wandor	SL010216	0.26	0.26	0.55	0.40	0.45	0.46
Tunkia	SL010215	0.53	0.54	0.64	0.60	0.64	0.41
Kenema Town	SL010291	0.99	1.00	NA	0.16	0.31	NA
Dea	SL010101	0.07	0.08	0.20	0.51	0.54	0.39
Jawie	SL010102	0.15	0.15	0.42	0.20	0.29	0.34
Kissi Kama	SL010103	0.06	0.05	0.36	0.47	0.49	0.53
Kissi Teng	SL010104	0.19	0.19	0.40	0.21	0.29	0.29
Kissi Tongi	SL010105	0.22	0.21	0.49	0.23	0.30	0.35
Kpeje Bongre	SL010106	0.12	0.13	0.39	0.12	0.23	0.29
Kpeje West	SL010107	0.24	0.24	0.40	0.46	0.51	0.39
Malema	SL010109	0.26	0.25	0.46	0.56	0.58	0.48
Mandu	SL010110	0.11	0.11	0.35	0.19	0.28	0.31
Gbinle Dixing	SL020202	0.24	0.17	0.32	0.68	0.59	0.44
Upper Bambara	SL010113	0.08	0.09	0.48	0.32	0.38	0.51
Jaiama Bongor	SL030107	0.17	0.18	0.27	0.39	0.45	0.30
Yawei	SL010114	0.20	0.20	0.46	0.26	0.34	0.36
Badjia	SL030101	0.09	0.09	0.35	0.24	0.32	0.36
Bagbwe(Bagbe)	SL030103	0.14	0.14	0.19	0.42	0.46	0.27
Bumpe Ngao	SL030105	0.23	0.24	0.41	0.49	0.54	0.43
Gbo	SL030106	0.11	0.12	0.19	0.39	0.45	0.28
Kakua	SL030108	0.20	0.21	0.30	0.17	0.28	0.17
Kalansogoia	SL020503	0.20	0.17	0.44	0.38	0.40	0.41
Marampa	SL020408	0.23	0.20	0.39	0.35	0.39	0.33
Lugbu	SL030110	0.16	0.19	0.65	0.42	0.50	0.65
Tikonko	SL030113	0.22	0.23	0.65	0.29	0.38	0.52
Niawa Lenga	SL030111	0.15	0.14	0.21	0.58	0.59	0.38
Maforki	SL020407	0.34	0.30	0.39	0.45	0.45	0.28
Wonde	SL030115	0.18	0.19	0.28	0.29	0.38	0.24
Bo Town	SL030191	0.38	0.43	NA	0.11	0.30	NA
Dibia	SL020403	0.20	0.14	0.15	0.53	0.49	0.25
Kunike Barina	SL020506	0.23	0.20	0.31	0.65	0.63	0.44
Gbonkolenken	SL020501	0.38	0.38	0.43	0.56	0.59	0.35
Kafe Simiria	SL020502	0.32	0.29	0.51	0.61	0.59	0.50
Malal Mara	SL020508	0.28	0.25	0.32	0.73	0.69	0.44
Kholifa Mabang	SL020504	NA	NA	NA	NA	NA	NA
Kholifa Rowala	SL020505	NA	NA	NA	NA	NA	NA
Kunike	SL020507	0.36	0.34	0.63	0.46	0.48	0.48
Dembelia - Sink	SL020301	NA	NA	NA	NA	NA	NA
Sambaya	SL020509	0.23	0.21	0.46	0.43	0.46	0.44

Tane	SL020510	0.22	0.21	0.40	0.35	0.40	0.34
Yoni	SL020511	0.61	0.59	0.73	0.66	0.65	0.45
Kaffu Bullom	SL020404	0.61	0.57	0.41	0.59	0.58	0.14
Lokomasama	SL020406	0.46	0.40	0.24	0.70	0.63	0.19
Masimera	SL020409	0.27	0.23	0.34	0.55	0.54	0.36
Sanda Magbolont	SL020410	0.26	0.20	0.55	0.47	0.44	0.51
Fiama	SL010301	0.05	0.05	0.16	0.31	0.37	0.27
TMS	SL020411	0.27	0.23	0.22	0.56	0.54	0.27
Lei	SL010307	0.09	0.08	0.34	0.14	0.24	0.29
Soa	SL010312	0.15	0.14	0.26	0.29	0.35	0.26
Gbane	SL010302	0.09	0.09	0.34	0.27	0.34	0.36
Gbane Kandor	SL010303	0.06	0.06	0.18	0.34	0.40	0.30
Gbense	SL010304	0.04	0.05	0.27	0.18	0.28	0.29
Kamara	SL010306	0.05	0.06	0.40	0.16	0.26	0.38
Mafindor	SL010308	0.05	0.04	0.36	0.32	0.37	0.45
Nimikoro	SL010309	0.15	0.14	0.32	0.22	0.29	0.25
Tankoro	SL010313	NA	NA	NA	NA	NA	NA
Koidu Town	SL010391	0.20	0.20	0.27	0.07	0.18	0.09
Nimiyama	SL010310	0.09	0.09	0.39	0.39	0.44	0.47
Sandor	SL010311	0.30	0.30	0.55	0.34	0.41	0.39
Toli	SL010314	0.00	0.00	0.21	0.04	0.16	0.20
Diang	SL020302	0.10	0.09	0.52	0.22	0.29	0.48
Folosaba Dembel	SL020303	0.10	0.08	0.50	0.12	0.21	0.41
Kasunko	SL020304	0.11	0.09	0.31	0.38	0.41	0.38
Wara Wara Bafod	SL020310	0.44	0.41	0.82	0.26	0.31	0.46
Mongo	SL020305	0.37	0.36	0.66	0.26	0.33	0.38
Neya	SL020306	0.63	0.61	0.90	0.40	0.45	0.44
Sengbe	SL020308	0.17	0.15	0.45	0.08	0.18	0.28
Nieni	SL020307	0.67	0.66	1.00	0.37	0.43	0.47
Mambolo	SL020204	NA	NA	NA	NA	NA	NA
Wara Wara Yagal	SL020311	0.08	0.06	0.45	0.00	0.10	0.31
Biriwa	SL020101	0.27	0.24	0.45	0.31	0.34	0.31
Gbanti Kamarank	SL020103	0.14	0.10	0.22	0.45	0.44	0.31
Bombali Sebora	SL020102	0.18	0.19	0.23	0.52	0.55	0.33
Gbendembu Ngowa	SL020104	0.23	0.18	0.35	0.41	0.41	0.33
Libeisaygahun	SL020105	0.18	0.13	0.27	0.48	0.44	0.33
Magbaimba Ndorh	SL020106	0.08	0.03	0.21	0.37	0.37	0.32

Paki Masabong	SL020108	0.21	0.22	0.22	0.54	0.59	0.31
Makari Gbanti	SL020107	0.28	0.27	0.31	0.42	0.46	0.25
Safroko Limba	SL020109	0.24	0.20	0.33	0.53	0.52	0.37
Sanda Tendaran	SL020111	0.16	0.11	0.20	0.45	0.43	0.29
Sella Limba	SL020112	0.30	0.27	0.74	0.33	0.37	0.55
Tambakha	SL020113	0.41	0.38	0.65	0.39	0.41	0.41
Makeni Town	SL020191	0.32	0.35	NA	0.18	0.32	NA
Magbema	SL020203	0.33	0.26	0.38	0.56	0.50	0.35
Masungbala	SL020205	0.21	0.17	0.53	0.46	0.46	0.54
Samu	SL020206	0.51	0.43	0.23	0.69	0.59	0.13
Tonko Limba	SL020207	0.28	0.23	0.40	0.47	0.45	0.36
Koya Rural	SL040101	NA	NA	NA	NA	NA	NA
Mountain Rural	SL040102	0.39	0.32	NA	0.40	0.37	NA
Waterloo Rural	SL040103	0.67	0.62	0.57	0.79	0.73	0.34
York Rural	SL040104	0.57	0.48	0.26	0.52	0.46	0.01
Central I	SL040201	0.47	0.25	NA	0.32	0.11	NA
East I	SL040203	0.47	0.30	NA	0.34	0.20	NA
East II	SL040204	0.51	0.33	NA	0.48	0.30	NA
Central II	SL040202	0.42	0.19	NA	0.32	0.11	NA
West III	SL040208	NA	NA	NA	NA	NA	NA
West I	SL040206	0.45	0.24	NA	0.16	0.00	NA
West II	SL040207	0.54	0.33	NA	0.32	0.13	NA
Gorama Kono	SL010305	0.13	0.12	0.33	0.31	0.38	0.35
East III	SL040205	1.00	0.96	NA	0.71	0.69	NA
Tasso Island	SL020405	NA	NA	NA	NA	NA	NA