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# Mapping Climate Vulnerability of River Basin Communities in Tanzania to Inform Resilience Interventions

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**Abstract:** Increasing climate variability and change coupled with steady population growth is threatening water resources and livelihoods of communities living in the Wami-Ruvu and Rufiji basins in Tanzania. These basins are host to three large urban centers, namely Dar es Salaam, Dodoma and Morogoro, with a combined total of more than 7 million people. Increased demand for ecosystem services from the available surface water resources and a decreasing supply of clean and safe water are exacerbating the vulnerability of communities in these basins. Several studies have analyzed climate projects in the two basins but little attention has been paid to identify locations that have vulnerable communities in a spatially-explicit form. To address this gap, we worked with stakeholders from national and local government agencies, basin water boards and the Water Resources Integration Development Initiative (WARIDI) project funded by USAID to map the vulnerability of communities to climate variability and change in the two basins. A generalized methodology for mapping social vulnerability to climate change was used to integrate biophysical and socioeconomic indicators of exposure, sensitivity and adaptive capacity and produced climate vulnerability index maps. Our analysis identified vulnerability "hotspots" where communities are at a greater risk from climate stressors. The results from this study were used to identify priority sites and adaptation measures for the implementation of resilience building interventions and to train local government agencies and communities on climate change adaptation measures in the two basins.

**Keywords:** climate change; climate variability; climate stressors; water resources; communities; vulnerability; hotspots; adaptation; resilience; GIS

## 1. Introduction

Increasing climate variability and change coupled with steady population growth are threatening water resources and livelihoods of communities living in the Wami-Ruvu and Rufiji River basins in Tanzania. The river basins are facing multiple climate threats, including increasing temperature, decreasing total rainfall and increasing rainfall variability [1–4], which are exacerbating uncertainties in fresh water supply. Steady population growth rate of about 2.7% [5] is increasing water demand. Additionally, competing uses of the water resources, such as increasing hydroelectric and agriculture in the two basins is further complicating efforts to manage this important resource. These issues threaten the health and livelihoods of communities in these basins and presents challenges to the governance of the water resources in the face of pressures from multiple water user groups. These threats are likely to continue to reduce the availability and quality of surface and groundwater resources. Sustainable and resilient governance of water resources will need to take into account threats from climate variability and change, as well as increased demand from a growing human population [6,7].

Climate sensitive water resource management is crucial to livelihoods in the two basins and therefore understanding their vulnerability to climate variability and change is crucial to the wellbeing of river basin communities [8]. These communities, especially in rural areas, are some of the poorest in the country with about one-third of the households considered multi-dimensionally poor (i.e., suffering deprivations in 33% of weighted indicators composed of health, education and standard of living) [9]. Sustainable utilization of the water resources in these basins requires sustained efforts to build the adaptive capacity of the social and ecological systems to existing and emerging threats.

Assessment of climate vulnerability, as a contribution to resilient and sustainable use of these resources by government and non-government actors, is an important source of information to the decision making process. Spatially-explicit vulnerability assessments can act as powerful decision support tools that provide a layer of information useful in the formulation of environmental policies [10–12]. In the recent past, the application of vulnerability mapping has grown tremendously, especially with the proliferation of mapping methods, increased data availability and a growing awareness and need to target responses to locations that need them most. Several vulnerability studies have demonstrated the importance of mapping and Geographic Information Systems (GIS) as powerful tools for identifying vulnerable communities and locations at different scales [13–20]. Vulnerability mapping entails the integration of indicators that act as proxies for different components of climate vulnerability of a system: (i) exposure to climatic stressors; (ii) sensitivity of the system to these stressors; and (iii) the adaptive capacity to cope with the stressors [21,22].

Vulnerability mapping that integrates biophysical and socioeconomic variables to support climate adaptation for vulnerable communities in Africa is not new. For instance, several studies have integrated climate variables such as extreme weather events to map climate hot spots [15,23] while other studies (e.g., [14,16–19]) have integrated climate variables such as increases in temperature, long-term changes in rainfall from historical observations, climate models and socioeconomic variables [23] to map areas where populations are vulnerable to climate extremes, malaria [20], floods and droughts [15,24] and conflicts. Because vulnerability is spatially differentiated [25,26], characterizing spatial variability in basin communities can aid identification of the most vulnerable locations. This type of information is useful because: (i) it provides the locations of such communities; and (ii) through additional analysis such as Principal Component Analysis (PCA), it can identify patterns in the input indicators that drive vulnerability in these communities to help target specific measures that reduce their sensitivities and build their adaptive capacity [27].

Several methods exist for spatially aggregating information into an index through the integration of spatial data layers. Each method has strengths and limitations and researchers have used various justifications for choosing an aggregation method. In recent meta-analysis, de Sherbinin et al. [13] performed a systematic review of 84 studies that mapped social vulnerability to climate impacts across the world. They found that the linear aggregation technique which includes averaging and additive approaches accounted for 50% of all studies. Other methods such as cluster analysis, geometric mean, geons and spatial regression modeling accounted for less than 25% of the studies. The averaging and additive approaches have been widely used because of their strength in summarizing information into simple indices that are easy to interpret and their robustness in transparency of aggregation methods [17,28].

Due to its broad use and application, it is important to give meaning to a vulnerability study by defining attributes that give reference to a specific vulnerable situation [29–32]. Füssel [30] suggested that vulnerability assessments need to identify the system of analysis, the valued attributes of concern, the external hazard and a temporal reference for the assessments to be meaningful. Our study identified these fundamental dimensions as follows:

- Focus: vulnerability of basin communities to climate stressors
- Valued attribute: water and food security, health and general wellbeing
- Climate stressors: variability and changes in rainfall and increasing temperatures that threaten social systems
- Temporal reference: historical period of 1981–2017

The objective of this study was to map and identify vulnerable communities to assist the United States Agency for International Development (USAID) funded Water Resources Integration Development Initiative (WARIDI) and local government partners prioritize climate adaptation interventions in the Wami-Ruvu and Rufiji basins. Ultimately, the broader outcome of this work was to support improved water resources management and community livelihoods in the two basins.

## 2. Materials and Methods

### 2.1. Description of the Study Area

This study focused on the Wami-Ruvu and Rufiji River basins (Figure 1) where the WARIDI project and national and local government agencies were jointly implementing projects to strengthen governance and resilient management of water resources and services under a changing climate.

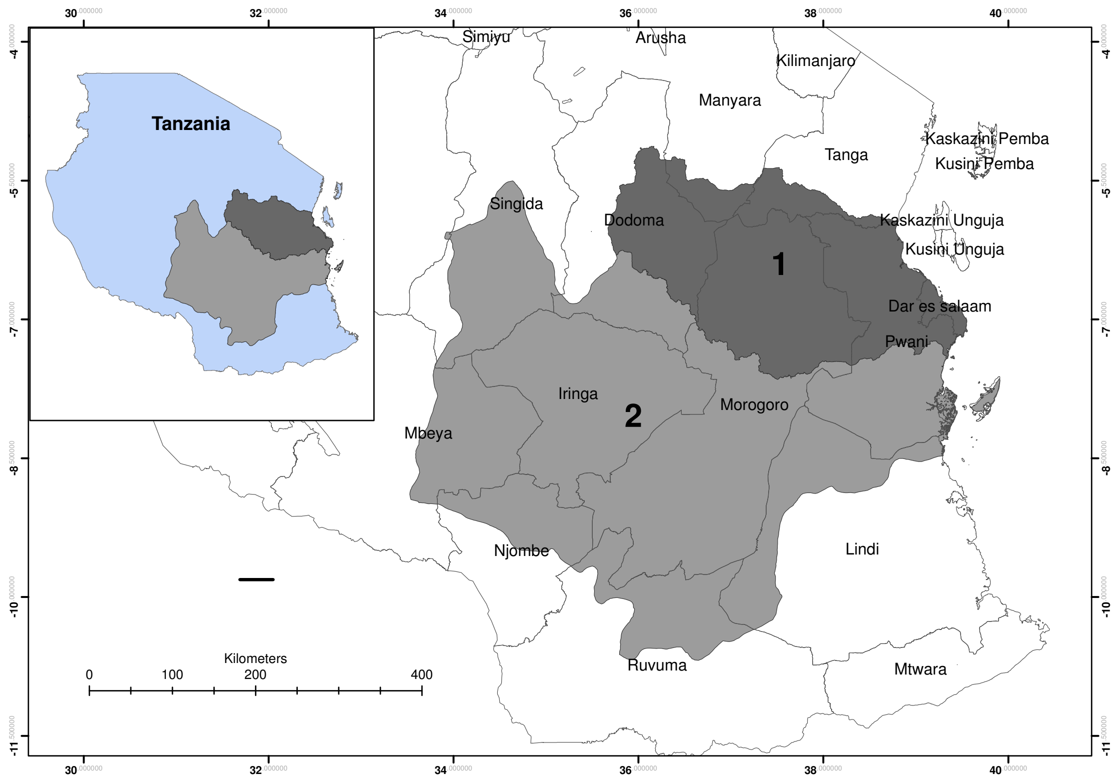


**Figure 1.** Map of the Wami-Ruvu (dark gray) and Rufiji (light gray) basins located in Eastern Tanzania. Inset: Location of the basins relative to the national boundary.

The Wami-Ruvu basin is estimated to cover an area of 72,930 km$^2$ and is primarily defined by the catchment of the Wami and Ruvu Rivers. It lies between longitudes 35°30′ and 40°00′ E and latitudes 05°00′ and 07°30′ S. The large urban centers of Dar es Salaam, Morogoro and Dodoma, are all located in this basin. A large climatic diversity exists within the basin: from humid plains along the Indian Ocean coastline and the high rainfall regions of the Eastern Arc mountains to the arid areas around Dodoma further west, which lie in the rain shadow of the mountains. The basin is the only permanent source of fresh water supply for the commercial capital city of Dar es Salaam which has an estimated population of more than 5 million people.

The Rufiji basin covers an area of about 177,420 km$^2$ (about 20% of Tanzania). It lies between longitudes 33°55′ and 39°25′ E and latitudes 05°35′ and 10°45′ S and comprises of four major rivers: Great Ruaha, Kilombero, Luwegu and Rufiji. The basin is also a power house of the country as it hosts the majority of hydropower plants in the country. A wide range of livelihoods exists in these basins including rain-fed and irrigated agriculture, pastoral livestock, tourism, forestry, fishing, mining and leading industries.

### 2.2. Stakeholder Engagement

Government and donor agencies are increasingly using vulnerability maps to prioritize the use of adaptation funding and resilience building areas [14,33,34]. Involving stakeholders in the development of vulnerability maps, especially in identification of drivers of vulnerability, selection of indicators and validation of end products, is a critical step to increase likelihood of use and buy-in of vulnerability maps [13,24,33,35–37].

To ensure this vulnerability mapping activity was done in a robust and inclusive manner, we formed an interdisciplinary co-development team (CDT) comprised of experts drawn from 12 government and non-governmental institutions (Table 1). The CDT drew its composition from members with expertise in GIS and remote sensing, statistics, hydro-geology, water resource and environmental engineering, cartography, climate change, livelihoods and community development. The CDT was actively involved, with three co-development meetings organized in the period of the mapping exercise. An additional stakeholder meeting with 47 participants was convened with decision makers from high level government and non-governmental agencies in order to obtain feedback on the vulnerability products as well as gather participatory recommendations on priority areas and strategic interventions for strengthening resilience of water resources and communities in both basins against climate variability and change.

**Table 1.** Institutions that formed the co-development team.

| Institution | Type |
|---|---|
| Ministry of Water | Government |
| Tanzania Meteorological Agency (TMA) | Government |
| Wami-Ruvu Basin Water Board | Government |
| Rufiji Basin Water Board | Government |
| National Bureau of Statistics (NBS) | Government |
| National Environment Management Council | Government |
| E-link Consult ltd. | Private |
| Wema Consult | Private |
| University of Dar es Salaam- Institute of Resource Assessment | Academic |
| President's Office, Regional Administration and Local Government | Local Government (PO-RALG) |
| Planning Commission | Government |
| USAID Water Resources Integration Development Initiative (WARIDI) | Donor funded project |
| Regional Centre for Mapping of Resources for Development (RCMRD) | Intergovernmental |

### 2.3. Vulnerability Mapping

#### 2.3.1. Data Sources and Indicator Selection

We used a range of remote sensing, modeled and socioeconomic data as well as vulnerability indicators in this study, as listed in Table 2. Indicator selection was done through a process of compiling an initial list of potential candidates by the CDT and further refined through the stakeholder consultation meeting that included experts from five water user groups: agriculture, water, communities, water, sanitation and hygiene (WASH), energy and terrestrial ecosystems. The refinement was further complemented by an evaluation criteria that guided data collection. We evaluated data in terms of:

1. Availability and accessibility: The study used data that were available and accessible at the time of analysis.
2. Conceptual proximity to the component being measured: Data had to be associated with one of the three components of vulnerability and the scope of the vulnerability mapping.
3. Spatial resolution: Gridded data had to have high resolution ($\leq$5 km$^2$) while socioeconomic data from household surveys had to be disaggregated to ward level and not larger than a district.
4. Timeliness of most recent acquisition: Climate data had to cover the period 1981–2017 while environmental and socioeconomic data had to be 10 years old or less.
5. Reliability and validity: Data had to be consistently representative and accurate for each indicator.

**Table 2.** The list of indicators used to compile component and overall vulnerability indices.

| Component | Indicator | Variable | Data Source |
|---|---|---|---|
| Exposure | Precipitation change | Long term trend in annual precipitation | CHIRPS enhanced precipitation for Wami Ruvu and Rufiji basins (1981–2016) |
| | Precipitation variability | Long term Coefficient of Variation in annual precipitation | CHIRPS enhanced precipitation for Wami Ruvu and Rufiji basins (1981–2016) |
| | Floods | Flood frequency (events/100 years) | UNEP GRID (2009) |
| | Temperature | Long term mean of annual maximum temperature | FEWSNET ITE temperature (1981–2012) |
| Sensitivity | Soil health | Soil organic carbon | FAO-ISRIC Global Soil Organic Carbon Map (2017) |
| | Poverty | Poverty index | National Bureau of Statistics (2016) |
| | Child mortality | Under 5 mortality rate | National Bureau of Statistics (2015) |
| | Malaria susceptibility | Malaria endemicity index | Malaria Atlas project (2010) |
| | Population | Population count/ward | National Bureau of Statistics (2012) |
| | Land use land cover | Land use land cover change | RCMRD (2010) |
| Adaptive capacity | Crop productivity/Yields | Water Requirement Satisfaction Index (WRSI) | FEWSNET GeoWRSI (1981–2016) |
| | Water access | Access to safe drinking water | National Bureau of Statistics (2015) |
| | Markets | Access to market services (travel time) | JRC World travel time map (2015) (Weiss et al., 2018) |
| | Availability of health services | Health infrastructure index | DHS (2015) |

The climate exposure indicators comprised of average conditions for temperature as well as long-term variation and changes in rainfall. Flooding was also included because it is regular occurrence in the two basins. Rainfall and temperature data were sourced from a locally enhanced Climate Hazards InfraRed Precipitation with Stations (CHIRPS) and an interpolated temperature provided by the Famine Early Warning Systems Network (FEWSNET), respectively. CHIRPS is a $\geq$35 quasi-global rainfall dataset that blends satellite estimates and in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring [38]. The locally enhanced CHIRPS and temperature data incorporated additional in-situ stations provided by TMA.

Flood frequency data were sourced from the United Nations Global Risk Data Platform (GRID). This dataset included a modeled estimate of flood frequency at 1 km$^2$ spatial resolution. The data are derived using a combination of GIS and hydrological modeling using the HydroSHEDS dataset and the Manning equation [39] to estimate river stage for a calculated discharge value. It also integrates observed flood events from 1999 to 2007. This data represent the expected average number of events per 100 years [40].

Soil organic carbon (SOC) was sourced from the Global Soil Organic Carbon Map (GSOCmapV1.0) mapped by FAO [41]. This product consisted of national SOC maps, developed as 1 km soil grids, covering a depth of 0–30 cm. Organic carbon (OC) in soils is an important determinant of crop yields and higher OC content would be associated with high soil water retention [42], hence lower sensitivity to climate variability [43]. Additionally, we used the FEWSNET GeoWRSI tool [44] to calculate potential for maize yields from 1981 to 2016. Maize is a major subsistence and cash crop for communities living in these basins. Areas with low yields potential were categorized to have higher sensitivities to climate variability and hence communities living in those areas were considered more vulnerable.

Malaria prevalence index data covering the period 2000–2015 was sourced from the Malaria Atlas Project (MAP) [45]. These data provide the prevalence of *Plasmodium falciparum*, the malaria causing parasite, by combining environmental data and survey point data of clinical malaria incidences, parasite rates and reconstruction of changing interventions. The output data were the *Plasmodium falciparum* parasite rate in 2–10 year olds in Africa averaged over the time series at 30 arc-second resolution.

Land use and land cover data were provided by the RCMRD. This product was generated using Landsat imagery at 30 m resolution and changes were calculated from the year 2000 to 2010. The product was generated using the IPCC classification system complemented by nationally-defined land cover classes [46].

A Demographic and Health Survey (DHS) carried out in 2015 together with integrated household surveys from 2012 to 2016 provided socioeconomic indicators: poverty index, child mortality rates, population counts, access to improved water sources, and availability of health services (in form of geographical distribution of health infrastructure). These datasets were collected from the NBS portal. Accessibility data (travel time to major towns) were sourced from MAP [47]. These are newly released 30 arc-second resolution data that characterize travel time (in minutes) to major towns or cities. They are an improvement on an earlier global accessibility map created by the European Commission Joint Research Centre (JRC) in 2008. Accessibility is essential to meeting economic needs of a population and can be a limiting factor to access schools, markets, health centers, water sources such as boreholes and governance institutions. Physical isolation is a barrier to poverty reduction and improvement of community livelihoods essential building for adaptive capacity to cope with environmental stresses. Physical isolation also deprives poor communities who are mostly in rural areas of essential services that are available in major towns and cities.

### 2.3.2. Aggregation of Vulnerability Indicators

A generalized function (Equation (1)) was adapted from the Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) conceptual framework for climate change vulnerability assessments [48] to develop composite vulnerability indices.

$$Vulnerability = f(Exposure, Sensitivity, Adaptive\ Capacity) \quad (1)$$

This framework is widely used due to its ability to create separate maps for each vulnerability component and has the potential to help decision-makers analyze adaptation options [25,49].

A spatial index approach was used to aggregate indicators into components, and components into overall vulnerability. Maps created through this approach are advantageous in that it is easy to communicate complex information [17,50,51], although aggregation, while making it easy to interpret, can reduce the richness of information [27,52]. The additive approach was chosen [25] due to its relatively high degree of transparency in methods and the relative ease in summarizing and communicating results. However, even with these advantages, the method suffers from challenges in determining the relative importance of one indicator versus another. For this study, this challenge was addressed by subjecting our maps to validation by subject experts and local communities represented by officers from local government agencies.

Several data processing steps were followed to develop composite indices for overall vulnerability and the three components. First, all the original raw spatial layers were converted into grids of a common spatial resolution of 5 km$^2$. This grid resolution was chosen because the most complete data, the climate data, were at 5-km resolution and much of the socioeconomic data were aggregated at either district or ward level. The average size of wards and districts was 403 km$^2$ and 8705 km$^2$, respectively. To minimize redundancies introduced by indicators that are highly correlated, we performed a bivariate correlation analysis in order to identify and exclude indicators that were highly correlated from subsequent integration.

Each data layer was then transformed to an indicator with a range of 0–100 (with 0 and 100 representing least and most vulnerable, respectively). This transformation is an important step in data aggregation since raw data had different measurement units (e.g., rainfall (mm), temperature (°C), travel time to markets (minutes) and poverty (%)). This unit less scale was retained for component indices because the aggregation of indicators to the components resulted in varied ranges of scores based on the underlying distributions of the indicator scores [43]. In a few cases (e.g., population and access to markets), expert judgement was used to trim or winsorize values to a cut off point that became the maximum for that indicator, and values above this threshold were set to this maximum. In the case of population, the data were trimmed at 15,000 people, the mean population for wards in the two basins. This became the maximum value representing highest sensitivity in terms of number of people exposed to a climate impact such that the number of people per grid location above that threshold were not incrementally disadvantaged [43].

Winsorization was also applied to access to markets indicator, represented as the amount of time it takes to travel from one location to the nearest town of 50,000 people or more. These data were trimmed to a maximum of 3 h upon which we decided that any travel time over 3 h to access these towns for services had the least adaptive capacity (i.e., highest vulnerability score of 100). In other cases, an indicator such as land cover land use change data contained nominal data and categories of the change was directly assigned a value between 0–100 depending on the relationship between the change and the perceived importance to supporting community livelihoods. For instance, changes from vegetated categories to bare land were assigned 100 representing most sensitive categories (due to the sensitivity of open soil to erosion, high evaporation rates, lack of organic matter and low soil moisture to support vegetation or crop growth [53]). Additionally, some indicators have an inverse relationship with vulnerability and in those cases where high values in raw data were associated with low vulnerability (i.e., access to water, soil organic carbon, crop yields and health infrastructure), these values were inverted so that high and low values in raw data would represent low and high vulnerability, respectively [54,55].

Once the normalization was complete, the indicators were then averaged to produce overall vulnerability index. All data transformations and aggregations were performed in the R statistical package v3.4.2 while maps were produced in QGIS v2.8.1 and ArcGIS v10.1 as these were available to members of the co-development team.

### 2.3.3. Validation of Vulnerability Maps

This study engaged 150 representatives from local government agencies (LGAs) drawn from 20 districts where WARIDI was implementing resilience building projects. Validation exercises involved two general steps (Figure 2): (i) presenting draft maps to a team of thematic experts, mainly drawn from national level agencies, to provide initial input on the relevance of indicators, aggregation methods and communication of results from the vulnerability assessments; and (ii) presentation of refined maps to local community representatives at the LGA level based on the feedback from the national experts for validation of vulnerability hotspots and identification of adaptation options. A summary of this approach and the subsequent outcomes from the validation exercise are shown below.

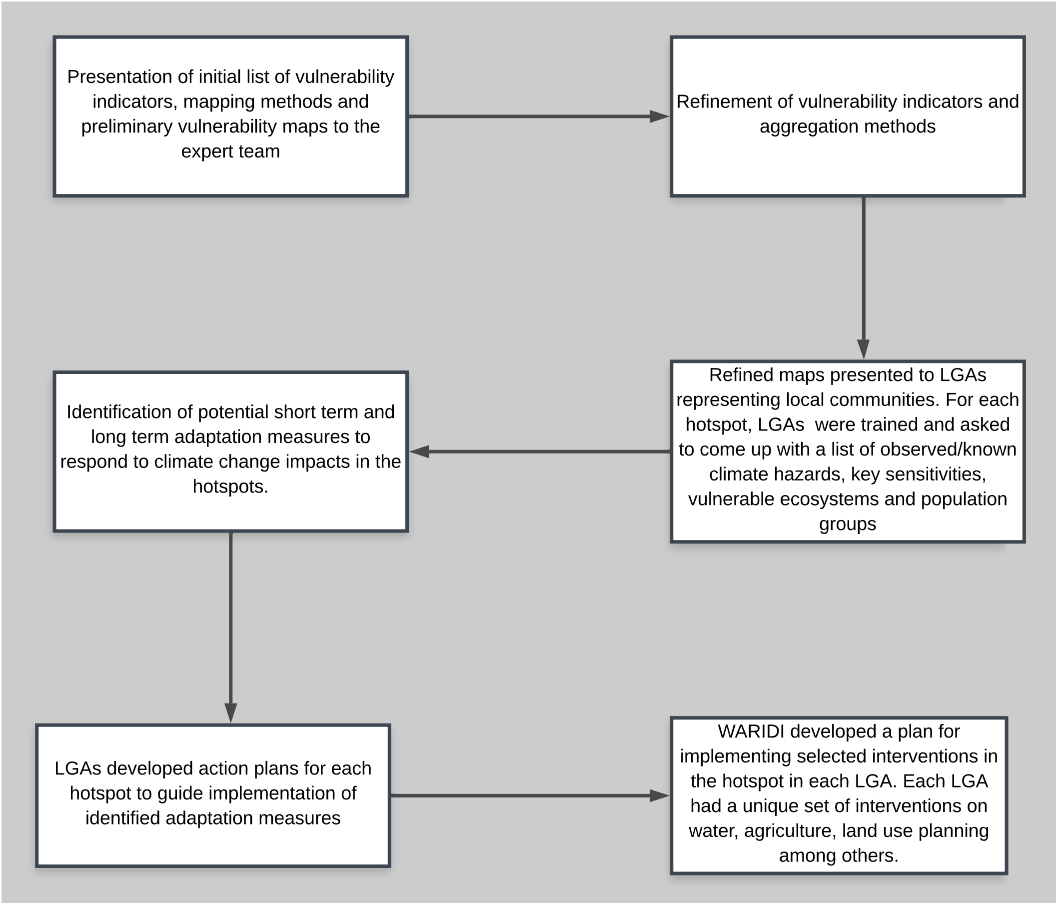


**Figure 2.** Steps used to validate the vulnerability hotspot maps.

In addition to showing the location of vulnerable communities, overall vulnerability was classified into five relative categories using equal intervals of 0–20, 20–40, 40–60, 60–80 and 80–100, and the total number of people living in those classes was estimated. A gridded population map [56] was used to extract total population in each class using the ArcGIS v10.1 zonal statistics tools. This information was useful to WARIDI and other stakeholders who required complementary information to support the maps in developing action plans and estimating the required funds to implement interventions.

Lastly, a cluster analysis was performed using aggregate scores for all districts in the two basins and a multidimensional scaling (MDS) plot to visualize the clusters was generated. This analysis summarized the relationship amongst districts and made it easier to identify similar districts in terms of their component scores and overall vulnerability. Radar plots of aggregate scores for three districts (Kilolo, Mvomero and Gairo) where WARIDI was primarily working, were also generated. This information provided a snapshot of how indicators and aggregate vulnerability indices scored in each district.

## 3. Results

### 3.1. Indicator Correlation

Pearson's linear correlation results did not show strong correlations between pairs of indicators (Figure 3). Consequently, all indicators were used in developing vulnerability indices. Significant ($p < 0.05$) but moderate negative and positive correlations between several pairs of indicators were observed. The precipitation trend indicator was negatively correlated with precipitation variability (R = −0.5), maximum temperature (R = −0.42), poverty (R = −0.37) and malaria susceptibility (R = −0.54). The health infrastructure index was negatively correlated with access to markets (R = −0.31) and crop productivity (R = −0.37). The total population indicator was negatively correlated with the access to markets (travel time) indicator (R = −0.26). Positive correlations were observed between the precipitation variability indicator and the maximum temperature indicator (R = 0.47), as well as between the maximum temperature indicator and the malaria susceptibility indicator (R = 0.38). The access to markets (travel time) indicator was also positively correlated with the crop productivity indicator (R = 0.31).

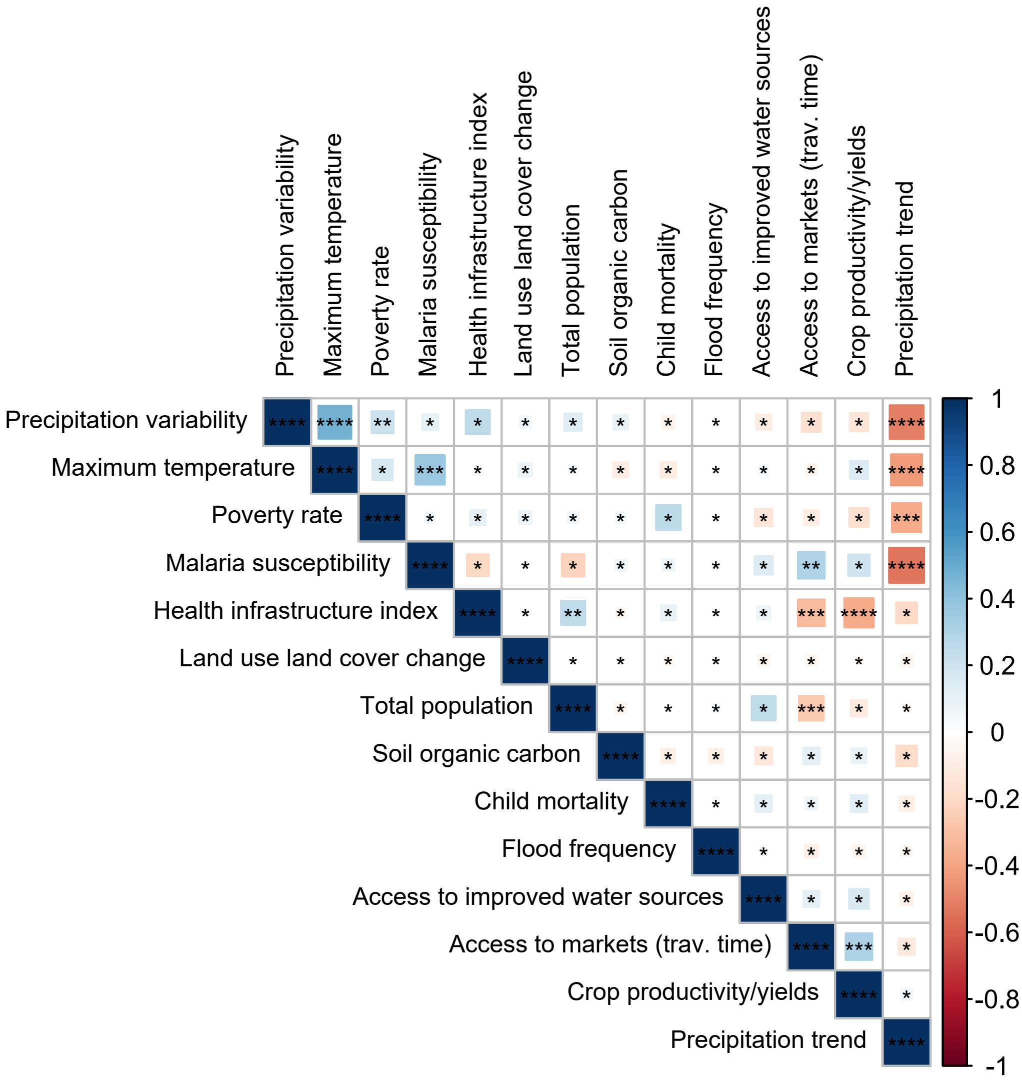


**Figure 3.** Pearson's linear correlation plot of vulnerability indicators. Square boxes show the strength of positive (blue) and negative (red) correlation (*R*) while asterisks show significance levels (*P*): 0.01 ****, 0.05 ***, 0.1 **, 1 *.

### 3.2. Exposure

The exposure index (Figure 4) was derived from precipitation trends and variability, long-term average maximum temperature and flood frequency. High exposure was seen in areas where the decline and variability in rainfall have been largest, areas with higher maximum temperatures and higher frequencies of flood events. Out of the four variables, flooding had little influence on the resultant exposure index (See Appendix A Figure A1). This is likely due to the fact that the flood indicator was derived from a modeled flood events output that focused mainly on rivers and streams. Highest exposure was observed in the eastern parts of the two basins and mostly in Rufiji districts of Ulanga, Kilombero and Rufiji; Wami Ruvu districts of Morogoro (rural), Mvomero, Gairo, Kilindi, Bagamoyo, Kibaha, Kisamawe, Kinondoni, Ilala, Temeke, Mkuranga and southern Handeni; and some pockets in Kongwa and Dodoma Urban.

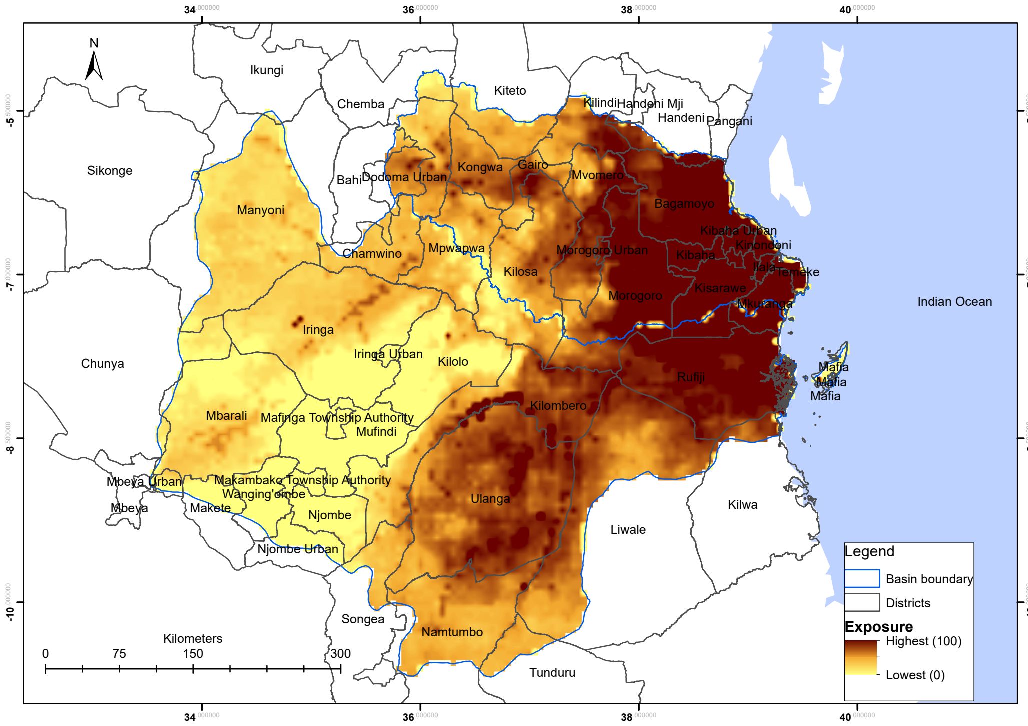


**Figure 4.** Map of the exposure of communities living in the Wami-Ruvu and Rufiji basins. The values have been stretched to one standard deviation to enhance colors.

### 3.3. Sensitivity

The sensitivity index (Figure 5) was derived from population, poverty, soil organic carbon, malaria susceptibility, child mortality and land use land cover change data. The most sensitive areas are located in Namtumbo, Ulanga, Kilolo, Kilombero, Morogoro, Mvomero and Bagamoyo; there were pockets of sensitivity in Kilosa, Liwale, Rufiji and Gairo, as well as rural areas in Mufindi, Iringa, Mbarali and Manyoni. All the indicators seem to have major influences on sensitivity in several locations in various ways (See Appendix A Figure A2). For instance, poverty and malaria seemed to influence sensitivity severity in Namtumbo, Liwale, Songea and the border areas of Mpwapwa and Kilolo districts. Child mortality and malaria susceptibility seemed to influence sensitivity in Morogoro while population seemed to be a major driver of sensitivity in many districts in the Wami Ruvu basin. Land cover changes considered detrimental for livelihoods and water resources were observed across many areas in both basins. Population on was a good indicator of sensitivity because highly populated areas are more prone to fresh water stress due to higher demand [57–59].

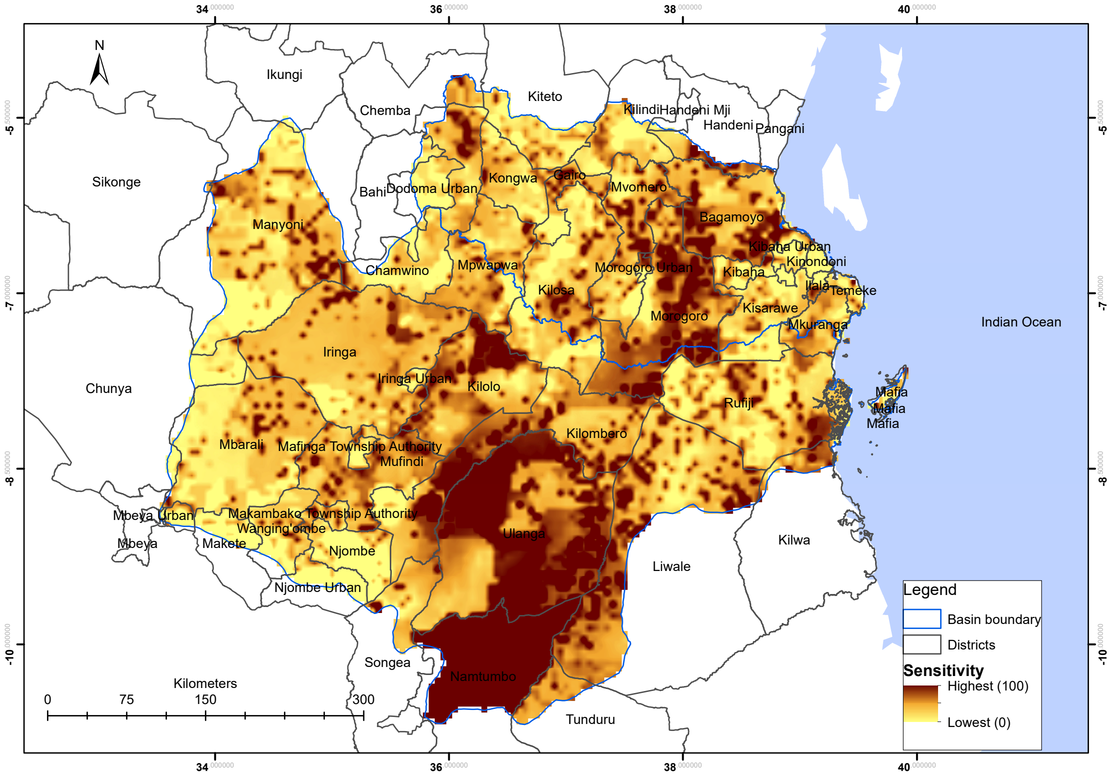


**Figure 5.** Map of the sensitivity of communities living in the Wami-Ruvu and Rufiji basins. The values have been stretched to one standard deviation to enhance colors.

### *3.4. Adaptive Capacity*

The adaptive capacity index (Figure 6) was derived from water requirement satisfaction index as a proxy for crop productivity, access to markets (travel time), access to improved water sources and availability of health services represented as health infrastructure index. Access to markets, availability of health services and access to water were dominant in the adaptive capacity index (See Appendix A Figure A3). Locations with low adaptive capacity in Wami-Ruvu basin were double those in Rufiji and most of these locations were in rural areas. Overall, districts with low adaptive capacity in both basins were Rufiji, Kilolo, Iringa Rural, Morogoro Rural, Bagamoyo, Chamwino, Mpwapwa, Manyoni, Kilindi, Kiteto, Gairo and some parts of Kilosa. Urban areas had relatively high adaptive capacity. For instance, even though most districts in Dar es Salaam city were in the high exposure category, their adaptive capacity index was high, resulting in low vulnerability. Populations in these districts had good access to markets and health services and better access to improved water sources for domestic use. Overall, less than 50% of the population distributed across the two basins had access to improved water sources for domestic use. These populations were mostly found in Iringa, Liwale, Rufiji, Njombe, Mufindi, Kilolo, Manyoni, Morogoro, Gairo, Kiteto, Kisarawe, Handeni and Mkuranga.

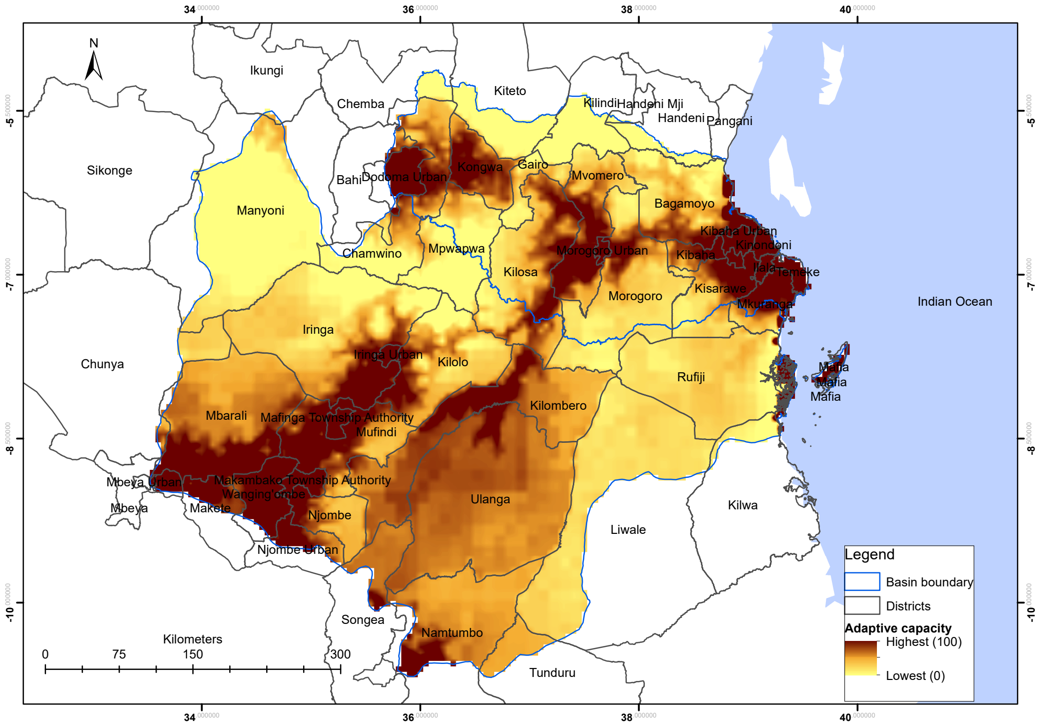


**Figure 6.** Map of the adaptive capacity of communities living in the Wami-Ruvu and Rufiji basins. The values have been stretched to one standard deviation to enhance colors.

### *3.5. Overall Social Vulnerability*

The overall social vulnerability map is shown in Figure 7. This map averages rescaled values from the exposure, sensitivity and adaptive capacity components. Generally, high vulnerability was in the eastern districts of the two basins. Areas of low vulnerability are in urban areas such as the big cities of Dar es Salaam, Morogoro and Dodoma, smaller urban centers and highlands in the southwestern districts of Rufiji basin. Districts with high vulnerability were Ulanga, Kilombero, Njombe, Kilolo, Liwale, Morogoro, Rufiji, Kisarawe, Manyoni and Kilosa, Gairo, Mvomero, Bagamoyo, Kibaha, some pockets in Iringa, Kongwa, Kiteto, Handeni Kilindi, Mkuranga, Temeke, Ilala, Kinondoni and Kisarawe.

Land area and population count statistics (Table 3) revealed that >80% of the land area and >60% of the total population in the two basins were in areas classified as medium-highest vulnerability. This category represents approximately 200,000 km$^2$ of land area and close to 8 million people. The highest proportion of land area and population was found in the medium category of 40–60% vulnerability (49% and 46%, respectively), representing approximately 120,000 km$^2$ of land area and close to 6 million people.

**Table 3.** Population count and land area statistics by overall vulnerability categories.

| SoVI (Equal Intervals) | Vulnerability Level | % Land Area | Total Population (2015) | Population % |
|---|---|---|---|---|
| 0–20 | Lowest | 2 | 1,058,367 | 9 |
| 20–40 | Low | 12 | 3,412,546 | 28 |
| 40–60 | Medium | 49 | 5,682,709 | 46 |
| 60–80 | High | 35 | 2,010,397 | 16 |
| 80–100 | Highest | 2 | 103,995 | 1 |

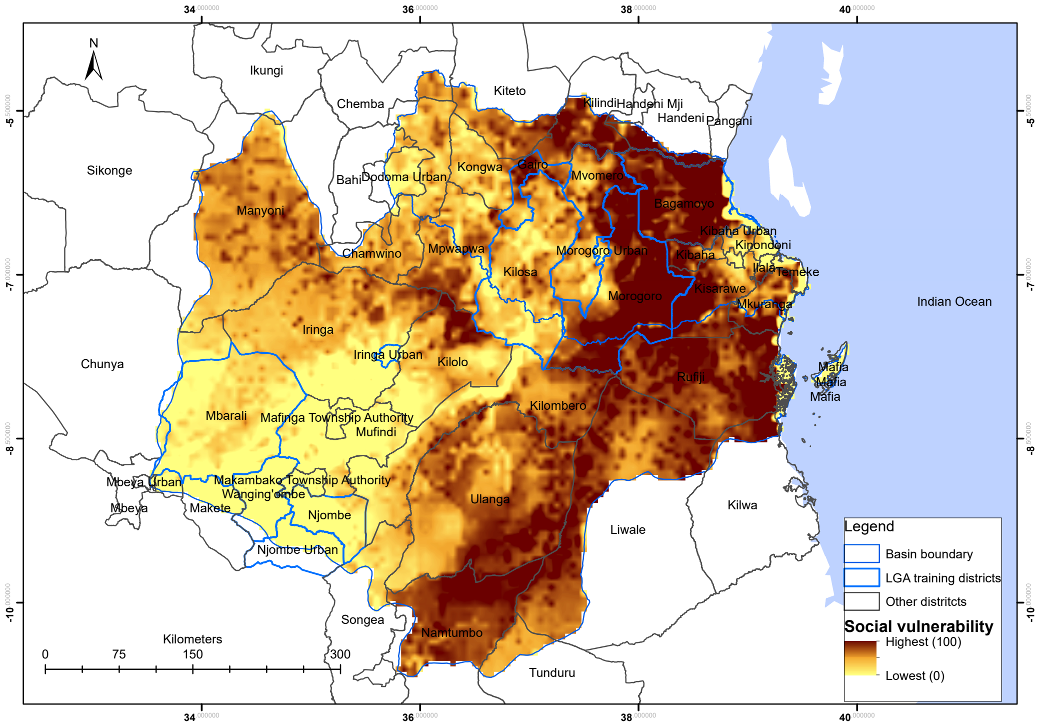


**Figure 7.** Map of the social vulnerability of communities living in the Wami-Ruvu and Rufiji basins. The values have been stretched to one standard deviation to enhance colors. Blue outlines are districts where WARIDI trained LGAs in climate change adaptation and multiple water-use services.

### *3.6. Selection of Hotspot Sites and Adaptation Interventions*

WARIDI was expected to work across 20 districts implementing resilience building interventions. The a priori site selection considered interventions for communities and water resources at the community and household level and were selected based on the following criteria: (i) buy-in from the community; (ii) support of the local government; (iii) complexity of the project; and (iv) the size of the population being served. The results shown in Figure 8 indicate that at 80% similarity, 50% of these districts were in the third tercile (highest vulnerability), 30% in the second tercile (medium-high vulnerability) and 20% in the first tercile (lowest vulnerability). Exposure and sensitivity were positively correlated with overall vulnerability while adaptive capacity showed a negative correlation. Districts in the first tercile and some in the second tercile were found to have relatively higher adaptive capacity and low vulnerability.

The results were also used by WARIDI in the selection of three vulnerable villages: Msufini in Mvomero district, Nguyami in Gairo district and Magana in Kilolo district (Figure 9). These three districts experience droughts and scored relatively high in mean daytime temperature. Kilolo district showed higher rainfall variability than the other two districts. Poverty scored highly (>40%) in all three districts with higher scores observed in Kilolo and Gairo. The latter was also highly populated and had higher scores in infant mortality rate, implying there were more deaths of children under five years. All three districts that this analysis identified had low scores for soil organic carbon, meaning their soils had high organic matter content suitable for agriculture because high soil organic carbon represented low sensitivity. All three districts scored poorly in availability of health infrastructure. Mvomero and Gairo districts scored highly in crop productivity.

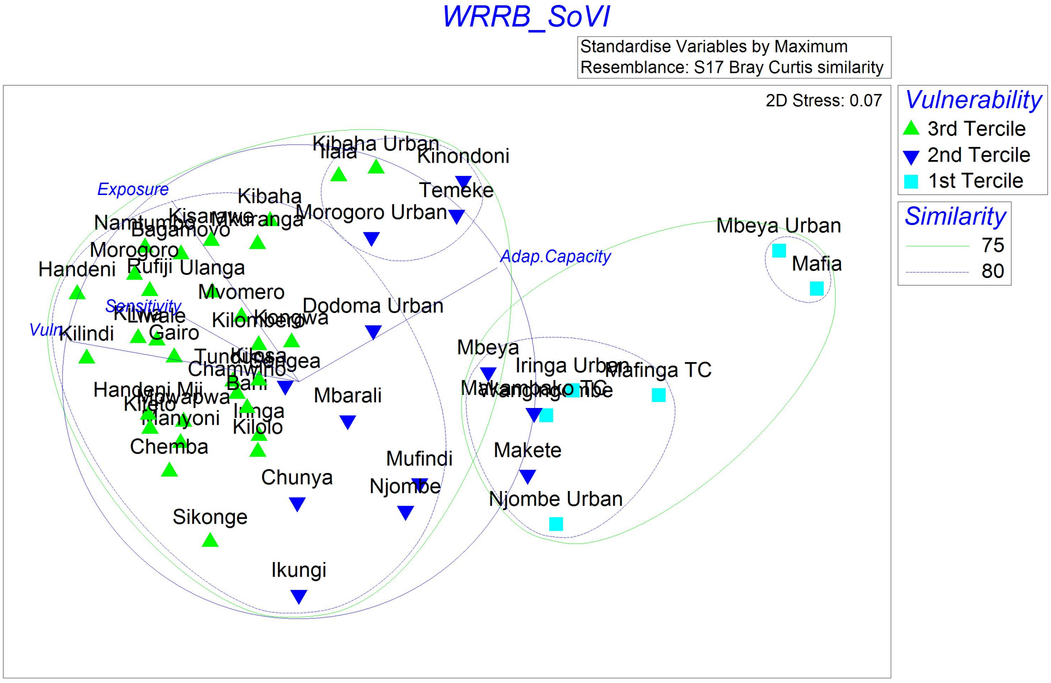


**Figure 8.** Multi-dimensional scaling (MDS) plot of overall social vulnerability. The trajectories show the correlation between vulnerability components.

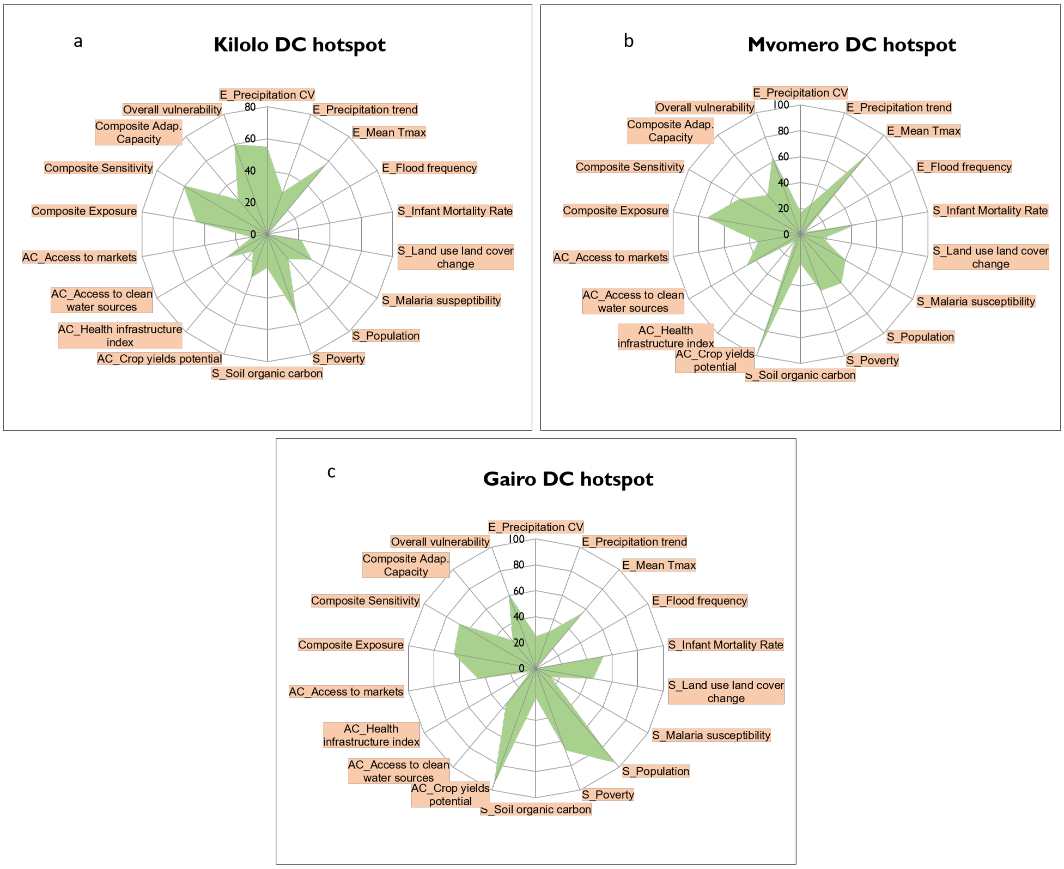


**Figure 9.** Radar plots of vulnerability indicators for three selected hotspot districts. E, "exposure"; S, "sensitivity"; AC, "adaptive capacity".

*3.7. Discussion*

Our study focused on generating information that would support prioritization of adaptation interventions in Wami-Ruvu and Rufiji basins using a combination of scientific methods and stakeholder engagement to map communities that were vulnerable to climate variability and change. The results show that these communities were found in areas which experience high exposure as a result of large rainfall declines and high variability coupled with higher temperature, higher sensitivity and low adaptive capacity. Overall, vulnerability maps from this study, regular consultations and engagement with local communities and district administrators provided a critical input to the selection of adaptation options that aligned well with community expectations. For instance, the consultations confirmed three villages as hotspots and identified land tenure as a way to support sustainable management of land, water and forest resources. As a result, WARIDI supported a participatory process with local governments and communities to develop and implement village land use plans (VLUPs) and record 1961 Certificates of Customary Rights of Occupancy (CCROs). In other locations, the vulnerability maps were used as one of several criteria for selecting the locations for 50 water projects which will supply clean water to 520,000 people. Communities surrounding the water supply projects were trained on water-efficient agriculture techniques and water conservation, particularly in dryer areas. Additionally, WARIDI worked with local technical assistance entities to train farmers on Climate Smart Agriculture (CSA) approaches such as crop diversification, agroforestry, improving soil organic matter and using small-scale intensified agriculture practices which improve water use efficiency.

Rainfall and temperature are major factors that influence the wellbeing of communities in Tanzania and East Africa in general. Our results show higher declines and higher variability in total annual rainfall over the past 30 years in the eastern parts of the two basins. This result is consistent with previous observations [1]. Rainfall decline has a direct implication on water availability in the two basins because major sources of water for various user groups come from surface water sources that depend on rainfall for recharge. Additionally, the eastern areas experience high temperatures and higher evapotranspiration. This observation raises concerns that high evapotranspiration and a declining rainfall will continue to exacerbate water stress, affecting surface water availability for both human and livestock, and reducing biomass and crop yields due to increased evapotranspiration [60]. This concern is further strengthened by observed land cover changes that impact water resources negatively such as deforestation for agricultural expansion. Deforestation removes vegetation cover that enhances water retention for surface water and regulates evapotranspiration. The rate of deforestation in the two basins has increased in the recent past. This has led to sedimentation of fresh water resources, increased surface run-off and flash floods and reduced the rate of infiltration, ultimately reducing base flows in rivers [61]. Future projections of temperature changes for Tanzania from most global climate models show an increase of 1–2 times the current increases in the near future (2020–2050) and 2–3 times in the mid and far future (2050–2100) for high greenhouse gas concentration scenarios [62]. Coupled with an increasing demand from high population growth, water security will continue to be a major concern for water user groups in these basins.

Sensitivity was observed to be higher in rural areas than in urban areas. Notably, malaria was dominant in the southern districts and along the coast south of Dar es Salaam city. Malaria is documented as a leading cause in child mortality in Tanzania, accounting for nearly a fifth of all deaths compared to other diseases, and the mortality rate has shown an increasing trend [63]. Temperature increase in the two basins has provided previously malaria free areas with conducive environments for vector carrying mosquitoes to thrive. We observed a positive correlation between malaria susceptibility and maximum temperature meaning, that areas that experience higher temperatures have a higher malaria risk. Steady population growth in both basins will further increase the number of people exposed to malaria.

Regionally, climate change has been attributed as a contributing factor to impacts on human health through increases in climate sensitive diseases like malaria [64,65] and other water-borne diseases such as diarrhea and cholera. Some of these impacts are already being experienced in some of the highlands in the rural areas of southern Tanzania such as Njombe, Kilolo and Mufindi which have witnessed increases in malaria and are some of the areas in the basins with low adaptive capacity to cope with malaria risk [66]. This information was corroborated by district officers during the validation exercises where warmer temperatures in these highland areas have been witnessed. Our results also show that availability of health infrastructure such as health centers is lacking or sparsely distributed in rural areas, leading to isolation of some communities from access to health services. Adequate preparedness for climate impacts on the health of communities in the basins will require local government agencies and other development agencies to strategically increase coverage of health services in rural areas in the two basins. This kind of intervention would minimize the isolation of vulnerable communities from health services. This will ensure that these communities have access to health services during crises occasioned by climate extremes such as floods and droughts and other longterm climate change impacts.

Enhancing the adaptive capacity of Wami-Ruvu and Rufiji basin communities to cope with climate shocks will require interventions in a number of areas. Agriculture is one of the major livelihoods in these basins, especially in the southern highlands of Rufiji basin. We observed that many rural areas were in locations that had potential for high crop yields but were in remote areas, taking longer duration to reach major market centers. This physical isolation can lead to negative consequences on availability of food for urban populations, precipitating increases in food prices. Rural farmers who cannot access markets for their produce can also suffer negative economic impacts, consequently affecting household income. The latter is a critical factor to the resilience of households during seasons that experience shocks such as droughts that affect crop yields. Overall, negative impacts on agricultural areas can have detrimental effects on the health and household vulnerability and likely undermine the ability to cope with future climate shocks. It is critically important for government and development partners to enhance the adaptive capacity of vulnerable communities in these basins to current impacts of rainfall declines on smallholder agriculture and availability of water resources for farming while also mitigating likely impacts from projected increases in temperature in the near future.

Our results provided an independent validation of selected districts and provided further evidence that a combination of quantitative and qualitative criteria can be used for prioritizing development assistance effectively. These results supported WARIDI's rationale for focusing on agricultural livelihoods and water resources management in each district hotspot. They also led to the development of district action plans for integrating climate change into district-wide development plans including interventions in agriculture, forestry, health, water, tourism and wildlife, and were used during facilitated discussions with national ministries including the Ministry of Water, Ministry of Agriculture, Ministry of Natural Resources and Tourism, Presidents Office—Regional Administrative and Local Government and local government authorities. It is worth noting that, while most of the interventions were in districts captured by our vulnerability maps as being hotspots, a good number fell in the lower categories of overall vulnerability. This can be partly explained by the choice of indicators which was influenced by our focus on social vulnerability. Our analysis captured various aspects in which different water user groups, largely comprised of the human population, are impacted by climate variability and other environmental changes. We defined these impacts as those that relate to health, wellbeing and livelihoods.

Temporally consistent climate data are important in climate vulnerability mapping and risk management [67,68]. Institutions in Tanzania led by TMA are increasing their capacity to collect and archive weather and climate data for use in climate risk and hydrological assessments. However, the capacity to analyze these data and integrate satellite Earth observations into their assessments is often limited with efforts have been ongoing to improve this capacity [69]. We used the co-development approach because it provided an opportunity for institutions in the CDT to collaborate in data analysis. It also acted as a means to build capacity of staff at institutions responsible for making data and information used in this study available for decision makers. This approach enabled technical experts in the CDT to work together by using good quality rainfall and temperature data that were generated through blending of station data with satellite proxies to produce vulnerability indices. The co-development team had an equally important role of providing insights on local conditions and supporting the linkage between WARIDI and other local stakeholders in government and other agencies.

Our data integration techniques involved combining high resolution satellite data with coarser resolution socioeconomic data. One advantage with satellite data is that they are consistent and cover vast areas. However, many of these data are proxies for factors that influence vulnerability. On the other hand, socioeconomic data provide data collected directly from household surveys. This means data are collected directly from subjects of a vulnerability study, thus providing better estimates of local conditions. However, even these have disadvantages because publicly available data are often aggregated at administrative units. In our case, most socioeconomic data were at the ward or district level. Comparatively, a grid pixel from the remote sensing data was 25 $km^2$ while the average size of wards and districts was 403 $km^2$ and 8705 $km^2$, respectively. Artifacts may arise from integrating data at different spatial scales such as abrupt discontinuities across borders may draw attention in differences between areas that are not necessarily present on the ground [43]. These caveats notwithstanding, the combination of remote sensing and household survey data is gaining popularity as one of the fast growing approaches being used in vulnerability mapping. Various publications have provided more critical perspectives on these approaches and describe in depth their limitations [13,17,43,54,66].

Other data integration challenges exist in vulnerability mapping. A major problem that data analysts in vulnerability mapping studies encounter is dealing with extreme values in data that may impact statistical operations. Through truncation or winsorization, analysts may overcome this challenge by limiting extreme values through statistical transformations. However, this winsorization has the potential to bias results. We encountered this challenge in the population and access to markets indicators and addressed it by combining expert judgement and existing literature on approaches to determining truncation thresholds. For instance, we limited the maximum amount of time to access major towns to 3 h based on international- and country-based recommended practices on access to health services. The World Health Organization (WHO) recommends that access to critical care should be within 2 h while some studies in sub-Saharan Africa have shown that many countries in Africa are yet to achieve this goal to guarantee universal access to healthcare [70]. By involving locally-based experts with sufficient knowledge of the geography of the study area and by subjecting our mapping outputs to validation by local communities, we were able to partially address the potential biases introduced by the data winsorization. We believe that the effect of data winsorization can only be fully assessed through a rigorous sensitivity analysis and validation. The interpretation of a vulnerability map should consider the fact that sections of the population may feel excluded from developmental programs because of the category they fall in from a mapping perspective, while it may not necessarily mean that they are not vulnerable; rather, the severity is not as high as that of populations in other higher categories. It is important to subject vulnerability maps to rigorous validation with people who understand the target region well to ensure that areas that do not look vulnerable on the map, but are on the ground, are captured when developing and selecting adaptation interventions.

Vulnerability maps can provide objective information for selection of sites for adaptive interventions but only if they are participatory and evidence-based. While they are useful in providing a systematic and reliable way to prioritize adaptation intervention sites, independently, they cannot be sufficient to ensure success in a resilience building activity. Building resilience is an incremental process that is influenced by political interests, availability of budget, motivation of local stakeholders and other factors. Our study provides evidence that the uptake of mapping results into decision making is highly dependent on a participatory process that gets buy-in from communities, key thematic experts, local government, and other stakeholders. The goal of a vulnerability mapping exercise is to identify locations or sections of populations that are most vulnerable and require development assistance to cope with existing and emerging stressors. However, this prioritization risks the shortcomings of excluding other sections of the population that may be identified as having lower vulnerability. It is important that development assistance activities using vulnerability mapping to inform decisions take into consideration both short- and long-term vulnerabilities to the population.

## 4. Conclusions

Our study demonstrated the value added by vulnerability analysis to prioritization of climate adaptation interventions in the Wami-Ruvu and Rufiji basins. We conclude that a data- and consultation-driven approach to vulnerability assessments provides more robust and evidence-based outcomes for prioritizing climate adaptation interventions. Such an approach also provides a systematic and objective process whose results create a record of data, outcomes, events and decisions that led to an intervention in a particular area. This provides a solid basis for decision making and policy interventions in highly vulnerable communities where resources are also scarce.

Since replicability of these prioritization processes in space and time is also important, and therefore reproducibility of results by research, policy and community-based institutions is also key, we also conclude that combining structured stakeholder engagement and scientific methods of data integration in mapping vulnerability is equally important in facilitating smooth uptake of the outcomes of vulnerability analysis studies. This builds the capacity to understand and analyze vulnerability both at community and research levels. We found that, to ensure transparency with our mapping methodology and to build lasting capacity of local experts in replicating this type of mapping in future, it was critically important to form a co-development team. This was important in sustaining the interest of the team and supporting effective dialogue and prioritization of development assistance activities between WARIDI and a broad range of stakeholders.

**Author Contributions:** The lead author (D.M.) wrote this article with inputs from the co-authors, who were instrumental in the development of the original report. E.K., L.K. and A.W. contributed to the methodology, facilitated stakeholder engagements and validation while G.K. and L.N. participated in data collection, analysis and training of the local co-development team. R.M. contributed to the drafting, review and editing of the article. All authors have read and agreed to the published version of the manuscript.

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## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| AC | Adaptive Capacity |
| CCRO | Certificate of Customary Rights of Occupancy |
| CDT | Co-development team |
| CHIRPS | Climate Hazards InfraRed Precipitation with Stations |
| CSA | Climate Smart Agriculture |
| DHS | Demographic Health Surveys |
| FAO | Food and Agriculture Organization of the United Nations |

| | |
|---|---|
| FEWSNET | Famine Early Warning Systems Network |
| GIS | Geographic Information Systems |
| GRID | Global Risk Data platform |
| GSOCmap | Global Soil Organic Carbon map |
| IPCC | Intergovernmental Panel on Climate Change |
| ISRIC | International Soil Reference and Information Centre |
| JRC | Joint Research Centre |
| LGA | Local Government Agency |
| MAP | Malaria Atlas Project |
| MDS | Multi-Dimensional Scaling |
| NBS | National Bureau of Statistics |
| OC | Organic Carbon |
| PCA | Principal Component Analysis |
| QGIS | Quantum GIS |
| RCMRD | Regional Centre for Mapping of Resources for Development |
| SoVI | Social Vulnerability Index |
| TMA | Tanzania Meteorological Agency |
| USAID | United States Agency for International Development |
| VLUPs | Village Land Use Plans |
| WARIDI | Water Resources Integration Development Initiative |
| WASH | Water, Sanitation and Hygiene |
| WHO | World Health Organization |
| WRRB | Wami-Ruvu and Rufiji Basins |

## Appendix A

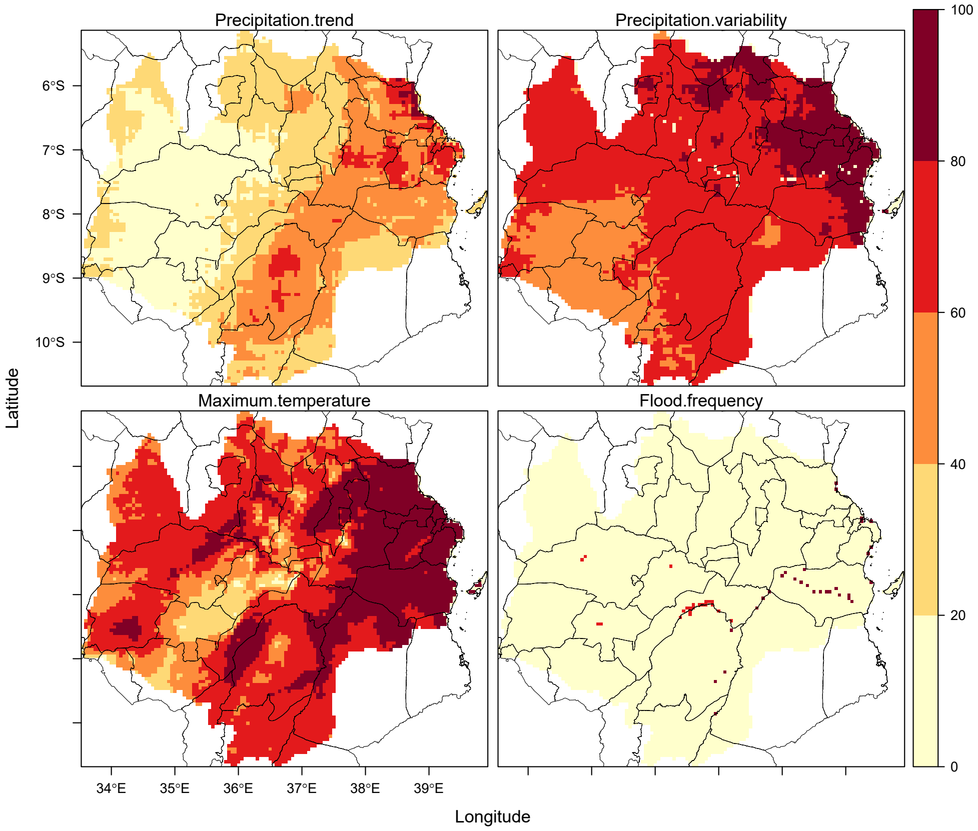


**Figure A1.** Plot of indicators used in this study to develop the exposure index.

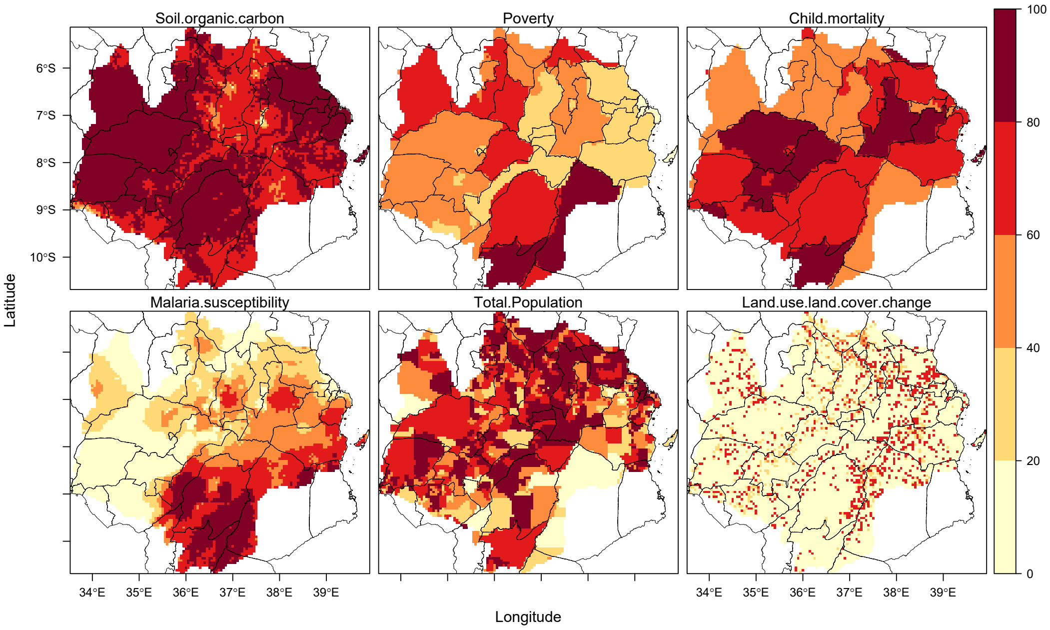


**Figure A2.** Plot of indicators used in this study to develop the sensitivity index.

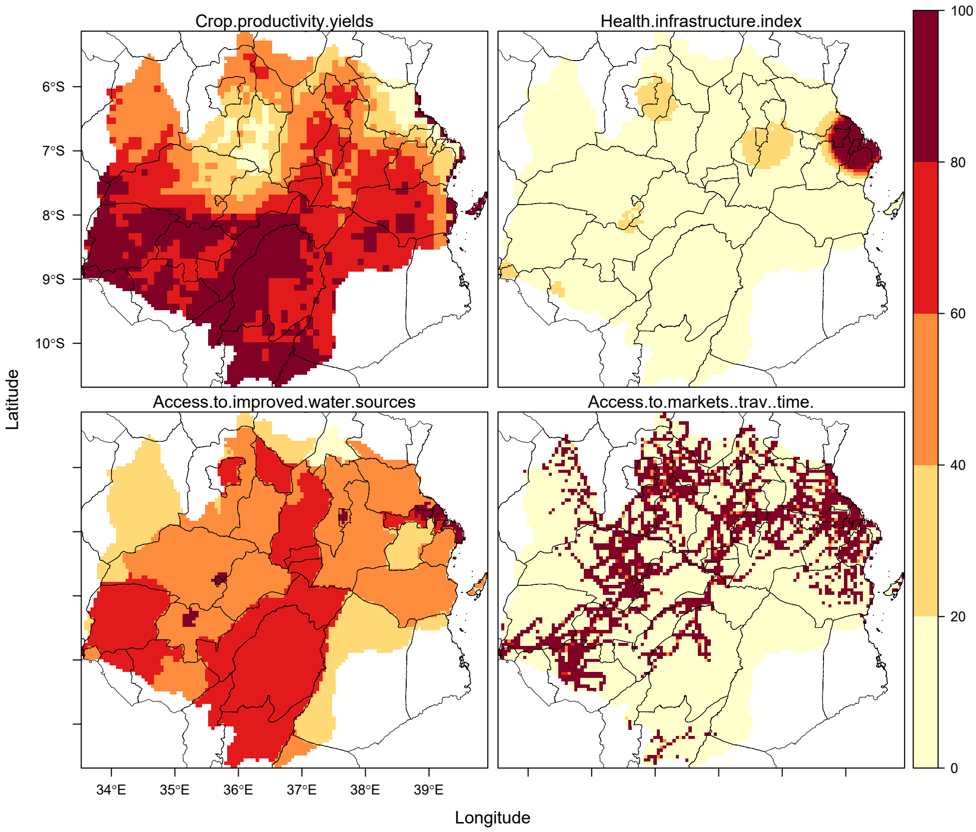


**Figure A3.** Plot of indicators used in this study to develop the adaptive capacity index.

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