



Climate change vulnerability assessment using a GIS modelling approach in ASAL ecosystem: a case study of Upper Ewaso Nyiro basin, Kenya

Grace Koech¹ · Godfrey Ouma Makokha¹ · Charles Ndegwa Mundia¹

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Abstract

Investments in climate change adaptation for communities and water resources are increasingly benefiting from vulnerability mapping. Such mapping can reveal hotspot areas from climate-related threats and can provide useful information needed for adaptation and resilience building efforts. The arid and semi-arid lands of Kenya are volatile to climate change and pastoralists in this region are highly dependent on climate-sensitive natural resources to sustain their livelihoods, hence any change in climate affects them negatively. This study sought to assess climate vulnerability in upper Ewaso Nyiro basin area using the IPCC approach which defines vulnerability in three components: exposure, sensitivity and adaptive capacity. Twelve indicators were selected based on its proximity to the component being measured and normalization of the indicators was done to ensure consistency of scale ranging from 0 to 100, illustrating a linear relationship to vulnerability 100 being most vulnerable. The study relied on averaging approach of indicators to derive component and vulnerability scores through the process of spatial integration. Results observed high vulnerability in areas exhibiting similar trend in high exposure and lack of adaptive capacity as well as high sensitivity. The highest vulnerability was observed in Korr/Ngurunit ward in Marsabit County where approximately 45.45% of the population was noted to be highly vulnerable to climate change impacts, while 54.55% of the population was noted to be moderately vulnerable. This study recommends county government and national government to build targeted resilience efforts within the highly vulnerable communities since this would improve community livelihoods.

Keywords Climate change · Vulnerability · Spatial analyses · Semi-arid

Background

The threats from climate change are becoming more evident over the years, and populations are under threat due to the dynamic nature of climate change risk which is increasing in frequency and severity. Various sectors and ecosystems globally are experiencing these impacts, hence leading to negative implications on the livelihoods, health and economy of different regions and landscapes (Polley et al. 2013).

Africa is already being affected by climate change, for instance in eastern Africa, it experiences severe droughts, famine, floods and increase diseases. The climate variability,

changes in the normal weather patterns and unpredictability, is impacting health, food security, agricultural production, energy, and water sectors hence affecting the ability of the African continent and especially East Africa countries to develop and grow (Besada et al. 2009).

The International Panel on Climate Change (IPCC) states in its Technical Report Climate Change that the changes observed over the 30 years, which defines climate change, are related to alterations in the hydrological cycle, which is a key driver of climate. Both seasonal and annual rainfall patterns in the world have been observed to change either in intensity, unpredictability and frequency. These changes negatively impact water catchment flows and river flow regimes hence affecting water resources, its quality and the biodiversity at large (Hall et al. 2012).

These changes will furthermore damage and affect human livelihoods, especially populations who directly depend on natural resources to sustain their livelihoods.

✉ Grace Koech
gracechero.gc@gmail.com

¹ Institute of Geomatics, GIS and Remote Sensing, Dedan Kimathi University of Technology, Nyeri, Kenya

Sectors such as water and sanitation, transport, rain-fed agriculture and irrigation will be adversely affected causing challenges in the population's health, economic status and security and increasing human populations especially in the developing countries will result to a higher demand for resources in a spatial–temporal manner (Nicol and Kaur 2016).

In Kenya today, climate change is being felt, its impacts are increasing in severity and frequency presenting challenges and risks to the populations and ecosystems (Ojwang et al. 2010). About 70% of Kenya is comprised of the arid and semi-arid areas, where millions of pastoralists and wildlife reside, this type of ecosystem is specifically important to the Kenyan economy since it hosts both wildlife and livestock population which are important to the economy of Kenyan, they are critical in providing earnings from foreign exchange (Njoka et al. 2016). The populations rely on good pasture for their livestock, therefore, when climate change alters the normal processes and properties of animal plants and vegetation, the populations and the ecosystem suffer (Mccollum et al. 2015). In the northern part of Kenya, the populations are affected by poverty where the poverty level is quite higher compared to the national average and specifically in the county Samburu, majority of the adults are illiterate and they face problems with water scarcity where about a third of the population cannot access clean water for drinking (Glew et al. 2010). It is, therefore, necessary to carry out a spatial investigation of the vulnerability of the community to climate variability and change, degradation and issues of water scarcity, since this study is able to locate the hotspot areas within the Upper Ewaso Nyiro ecosystem, and provide vulnerability maps that can be useful in informing decision makers and policy makers best suitable adaptation efforts where needed.

The most widely used method for undertaking vulnerability assessments and mapping is selecting key indicator variable that is aggregated together within different vulnerability component to produce a single index of vulnerability which is unit-less value (Abson et al. 2012). Quite a number of research on community vulnerability have been conducted in various areas in the world using various methodologies in different sectors and while narrowing down to Kenya, few studies have sort the use of geo-spatial technologies in assessing vulnerability especially in the Upper Ewaso Nyiro region. There is no study done in Upper Ewaso Nyiro that has sought to integrate the study of community livelihood vulnerability assessment based on issues of climate change and its vulnerability to the people while leveraging on geo-spatial approaches as well as the International Panel on Climate Change (IPCC) framework on vulnerability approaches. This research, therefore, adopts the International Panel on Climate Change (IPCC) framework and methodology for analysing vulnerability.

Development and analysis of vulnerability in this study, therefore, leveraged on the use of geo-spatial climatic, socio-economic and environmental datasets were integrated in a GIS environment to understand its interactions and its overall contribution to vulnerability. The study also assesses the suitable adaptation measures so that decision makers can be able to apply these measures in areas where the vulnerability index are high to improve resilience.

This spatial vulnerability modelling an elaborate integration of indicators in which geo-referenced socio-economic and environmental data, including those derived from earth observation technologies, are combined with climate layers to understand and assess vulnerability and, therefore, decision makers where adaptation is required (de Sherbinin et al. 2015). Data selection was be guided by expert judgement and literature review on factors known to closely associated to exposure, sensitivity adaptive capacity components, which enabled us to concentrate on the relevance and significance of the data to the overall vulnerability. The primary objective of this research is to assess climate vulnerability of communities in the arid and semi-arid lands areas of Upper Ewaso Nyiro basin to climate change.

Data and methodology

Study area

The Upper Ewaso Nyiro North river basin is part of the Juba basin, and covers an area of 47,655 km² in Kenya, Ethiopia and Somalia. The Upper Ewaso Nyiro North river basin is located to the north and west of Mt Kenya and extends between longitudes 36° 30' and 37° 45' east and latitudes 0° 15' south and 1° 00' north. The basin covers an area of 18,000 km², approximately 6% of Ewaso Nyiro North drainage basin and 2.8% of the total area of Kenya (587,900 km²) (Fig. 1).

Research design

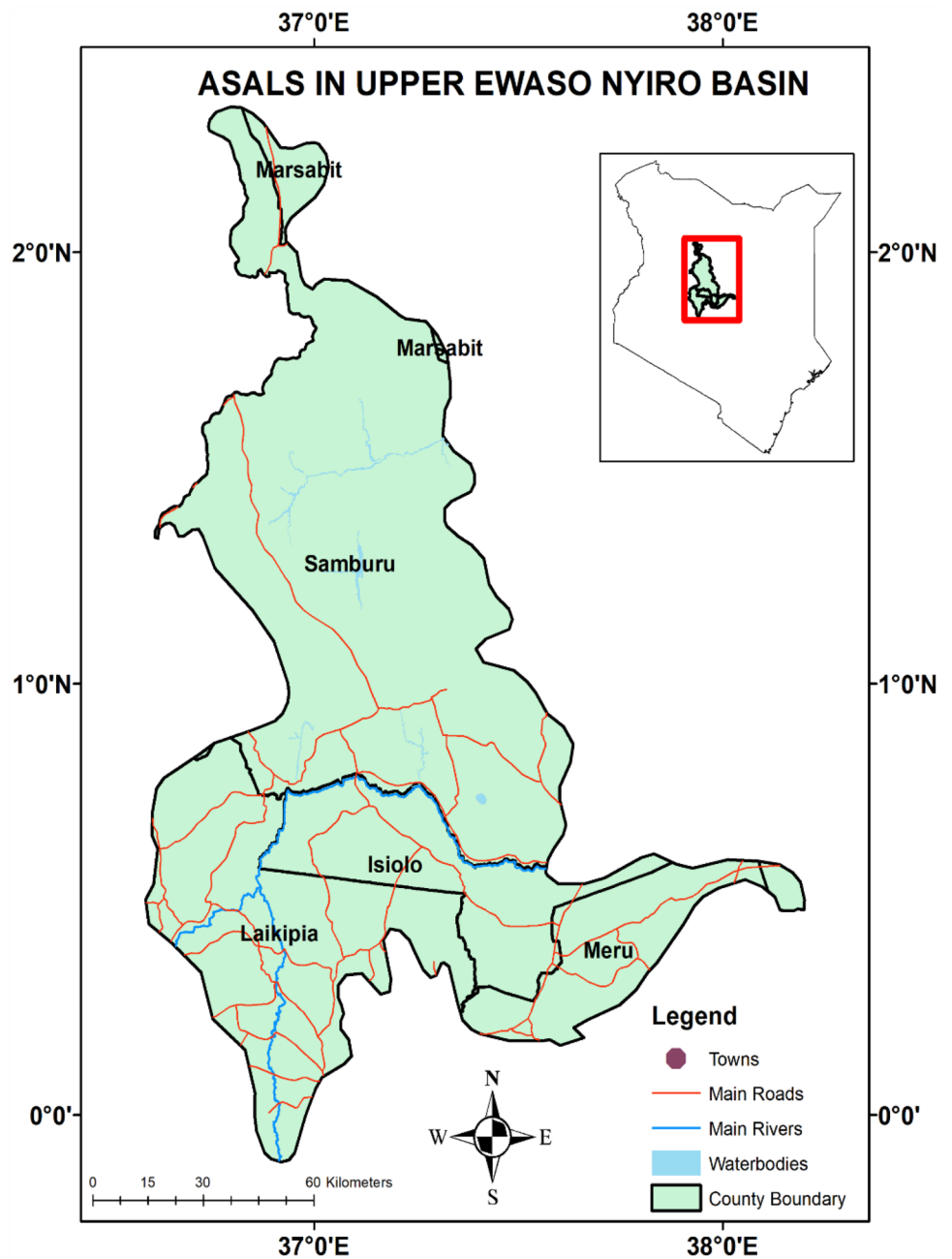
Methodology flow

The approach adopted for this study is summarized in Fig. 2.

Dataset

The study utilized a variety of available datasets for analysis, the data represented conceptual proximity to the component being measured. The guiding principle was to identify a limited number of high-quality spatial datasets that best represent the component of interest while avoiding the temptation to add low-quality data (data of high uncertainty or coarse spatial resolution) (de Sherbinin et al. 2015). The

Fig. 1 Study area



software and hardware requirements included, GPS, ArcGIS software, ENVI, ERDAS and R statistical program installed to facilitate the analysis. The datasets included rainfall data obtained from CHIRPS and temperature data from MODIS. Landuse/cover data were generated from Landsat satellite data as well as vegetation condition index obtained from MODIS NDVI. Population data, access to water, and education level data were all obtained from Kenya bureau of statistics, while market access 2015 was obtained from the Joint Research Centre (European Commission) (Table 1).

Analysis

Climate data

Monthly average for rainfall and temperature Statistical mean values or long-term averages were calculated in R studio and presented using graphs. Analyses on generating the average rainfall and temperatures were conducted to reveal general information on the overall estimated rainfall values over a period of 30 years.

Fig. 2 Methodology flow

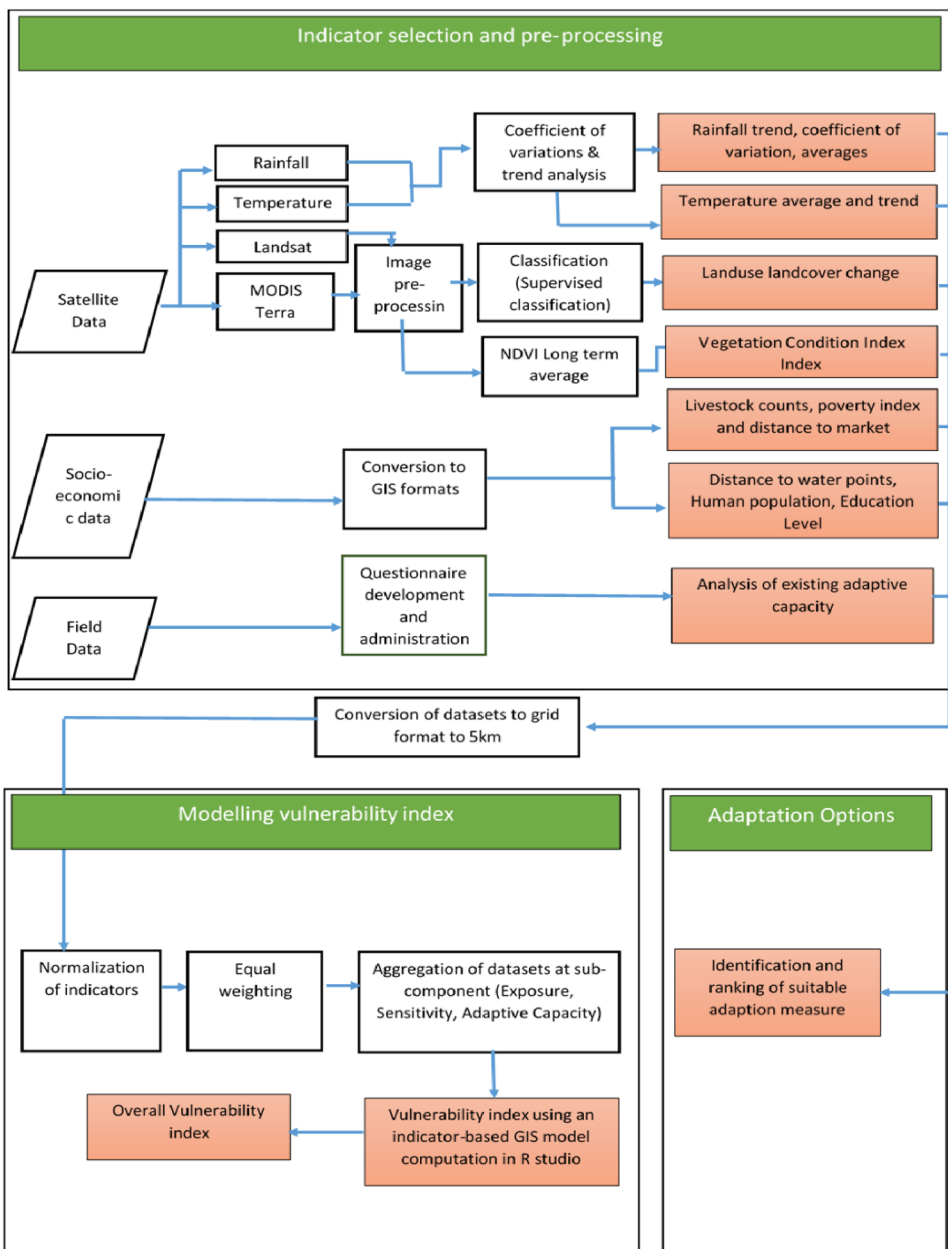


Table 1 Dataset required for mapping climate vulnerability

| Component | Data layer | Data sources |
|-------------------|--|---|
| Exposure | Coefficient of variation for precipitation | CHIRPS blended satellite-station precipitation |
| | Rainfall trends (change) | CHIRPS blended satellite-station precipitation |
| Sensitivity | Human population count | Kenya Bureau of Statistics (KNBS) |
| | Landuse landcover change detection | Landsat Imagery(1988–2018) |
| | Poverty level | OPHI Multiple Indicator Cluster Surveys Program |
| | Vegetation condition index | MODIS Terra NDVI (2000–2018) |
| | Livestock count | FAO Gridded Livestock of the World (GLW) |
| Adaptive capacity | Education level | Kenya Bureau of Statistics (KNBS) |
| | Market access | Joint Research Centre (JRC) World travel time map |
| | Improved clean water access | Kenya Bureau of Statistics (KNBS) |

Coefficient of variation for rainfall Standard deviation and coefficient of variation (% C.V) were calculated for rainfall to reveal the degree of seasonal and inter-annual rainfall variability of a locality using the following equation:

$$CV = (SD/Average) * 100. \quad (1)$$

Rainfall trend Analysis of 30-year trend was performed in R studio using the Sen slope, to identify locations where rainfall increases or decreases over time.

The formula of trend by slope of regression is presented in the following equation:

$$\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}) \div \left(\sum_{i=1}^n x_i - \bar{x}^2 \right). \quad (2)$$

Environmental datasets

The environmental and livelihood datasets included soil texture. Normalized Difference Vegetation Index (NDVI), livestock counts, population density/counts and landuse landcover. These datasets were used in determining the sensitivity patterns within the community, and its overall contribution to vulnerability.

Vegetation condition index data

NDVI was downloaded from MODIS/Terra vegetation indices MOD13A3 collection products. The data were clipped to the region of interest and mosaicked using ArcGIS 10.5. Images were rescaled by multiplying by 0.0001 to obtain the NDVI values. The monthly NDVI mean values were calculated, as well as the maximum and minimum values. The formula presented in Eq. 3 was then used to determine the vegetation index condition using the raster algebra in ArcGIS (Kogan et al. 2004)

$$VCI = 100 * (NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min}). \quad (3)$$

Landuse landcover change

Landuse landcover classification utilized Landsat ETM+ for the years 1988 and 2018. These images were downloaded from USGS earth explorer with the selection of the years based on the least cloud cover within the areas of study during analysis period. Image pre-processing steps were performed in ERDAS Imagine to remove the noise and perform atmospheric and geometric correction. Layer staking to combine the bands, re-projection

and clipping was undertaken. Land cover features were extracted through the use of supervised classification method. The number of classes were defined upon analysis, and the K nearest neighbour algorithm was adopted for the classification. Accuracy assessments were determined by comparing the classified images with higher resolution satellite data. ArcGIS was used to analyse the change detection maps for the years 1989–2018 from the classified images.

Livestock count

Livestock counts were downloaded from the Food and Agricultural Organization (FAO) Gridded Livestock of the World (GLW) as a raster file and further resampled to a 5 km resolution and projected to WGS 84.

Population count and poverty index data

These datasets were obtained from Kenya National Bureau of statistics at ward level as an excel document, the datasets were converted to a shapefile in Arcgis by loading the excel file into ArcGIS and joining the ward administrative shapefile data with the excel data at ward level. The shape files were then projected and resampled to a 5 km resolution and converted to a common grid/raster.

Projecting population data

For population, a projection analysis was performed since there was need to estimate current population numbers using the 2009 census population data.

The Global Population of the World (GPWv4) data for 2000 and 2015 were used to calculate annualized growth rates which were in turn used to determine population for target years at 1 km spatial grids. An average annual population growth rate between estimates was computed as follows:

$$r = \frac{\ln \frac{P_2}{P_1}}{t}. \quad (4)$$

Population estimates were calculated for target years using the following equation::

$$P_x = P_1 e^{rt}, \quad (5)$$

where r is the average growth rate, P_1 and P_2 the population estimates (totals) for the first and second reference years, respectively, and t is the number of years between the two population estimates (Balk and Yetman 2004). P_x is the population estimate in the target year.

Socio-economic data

Other critical datasets used for analysing adaptive capacity of the community included datasets on distance to markets (in terms of time taken to access markets), literacy levels of the population, improved water sources and health infrastructure index. These datasets were obtained from the Kenya National Bureau of statistics at ward level to capture the information at a relatively higher resolution. The datasets were converted from excel files to GIS shapefiles using ArcGIS software by joining the excel data with ward level administrative shapefile. These were then projected to WGS84, resampled to 5 km resolution and converted to a common grid/raster to overlay with the other datasets.

Primary data from questionnaire

To understand adaptive capacity for the communities with high vulnerability, a field survey was conducted by means of a structured questionnaire. This helped to capture the sentiments of the communities based on their existing coping strategies and its relevance to their livelihoods. A total of 150 questionnaires were administered to the residents within the study area at household level. A simple random sampling technique was adopted, and households within every ward were targeted to obtain representative information.

Data collection instrument included use of a closed-ended structured questionnaire, where the questions are divided into three groups: the first part considered the household characteristics, second part the livelihood strategies, while the third section investigated the climate change perceptions, while the fourth section sought to understand the socio-economic dynamics.

The households were selected randomly from the ASALs area of Upper Ewaso Nyiro basin. The total number of the selected population interviewed was determined by the following formula:

$$N = N \div (1 + N e_2), \quad (6)$$

where n is the sample size between 5 and 10%; N is the total number of households in the area; and e is the desired margin of error.

Data integration

The components of vulnerability according to IPCC entails the procedures discussed above, and it was necessary to undertake analysis on each component separately to understand for instance how a community is exposed to climate change, and how sensitive they are to it as well as their adaptive capacity levels.

The exposure component included all aggregated climate indicators that included rainfall trends, rainfall coefficient of variation, rainfall averages, temperature trends and temperature average. Sensitivity indicators included human population projection counts (2018), livestock counts, vegetation condition index, landuse landcover change, education levels and poverty index. For lack of adaptive capacity, the indicators included access to market and improved water access. These indicators were aggregated at every component level to develop the index.

Modelling vulnerability index

A fishnet (centroids) of the basin shape file was created to have regularly spaced grids of sampling points inside a polygon layer.

Values of all the raster layers were extracted to the centroid points using the spatial analyst tool (using extract multivalues to point tool) then creating a text file with the values extracted for analysis in R studio. The text file was obtained and saved as a csv, since R studio works with csv text files. In R studio, normalization approach was undertaken for each indicator, owing to problems of incommensurability in measurement units of the raw data, the values for each layer were normalized to a consistent ordinal or unit-less scale (e.g., rainfall averages or poverty levels on a scale from 0 to 100, from lowest to highest).

All the datasets were transformed to a consistent scale from 0 to 100. 0 representing the lowest vulnerability and highest of 100 to represent highest vulnerability across all components, exposure sensitivity and lack of adaptive capacity. Different indicators translated differently to overall vulnerability for instance a high temperature trend (increase in temperature over time) would mean a high vulnerability to the community thus a direct relationship while average rainfall would have an inverse relationship to vulnerability, because a high average value would mean its beneficial to the community since they could access rainfall water, adequate pasture and crops. The formula used normalizing the indicators was set as

$$\frac{(x - x_{\min})}{x_{\max} - x_{\min}} * 100, \quad (7)$$

where x is the indicator and x_{\max} and x_{\min} are the maximum and minimum values of the indicator x , respectively.

In some cases, indicators that have high scores were associated with low vulnerability (e.g., high adult literacy rates representing high adaptive capacity and consequently, low vulnerability) and these indicators were inverted so that the meaning of low and high remained consistent across all aggregation levels (indicators,

components and overall vulnerability). The formula given in Eq. 8 was used to invert indicators that have an inverse relationship to vulnerability is shown below:

$$\frac{(x_{\max} - x)}{x_{\max} - x_{\min}} * 100. \quad (8)$$

R statistical software was used to maximize on its powerful capability in statistical analysis and tabular visualization and processing. To remove redundancies in indicators that were highly correlated, a bivariate correlation analysis was undertaken to identify and exclude indicators that were highly correlated from the analysis. The rescaled indicator layers were averaged or added together to derive component and vulnerability scores. The IPCC definition of vulnerability is the most frequently used framework, and one advantage of this approach is that separate maps for each vulnerability component (e.g., into exposure, sensitivity and adaptive capacity) could help decision makers to analyse adaptation options. This approach assumes a linear relationship amongst indicators and the component of vulnerability being measured.

The formula adopted for vulnerability is given in the following equation:

$$\text{Vulnerability} = \text{Exposure} + \text{Sensitivity} + \text{Lack of adaptive capacity}/3. \quad (9)$$

Identification of suitable adaptation measures

Through the assessments of adaptation information from the questionnaire, existing adaptation strategies was identified taking stock of the strategies that were working and those that were not effective, the challenges and the solutions by the community on how best they could be assisted by the government and local organizations to improve on their coping strategies.

Ethical considerations

Proper ethical procedures were duly followed during the data collection, where ethical and data protection requirements were followed as required.

Results and discussion

Assessment and identification of key indicators

Exposure component analysis

See Figs. 3 and 4.

Rainfall average, variability and trend

The exposure component analysis was composed of precipitation average, trends and variability. The region was observed to have two rainfall seasons both the long-term March, April and May season and the short-term rainfall October, November and December as per the rainfall pattern in Fig. 1. The highest rainfall amounts was seen in 2018 at 9096 mm for 10,501 mm for the OND season during 1997 El nino events seen in the entire country. 1987 had the minimal rainfall during the OND season at 2436 mm and 1574 mm for the year 2000 during the MAM season. As observed in the seasonal rainfall variability graph in Fig. 1, there was much variability in rainfall especially in the year 2014 which has the highest variability of 45% recorded during the long rains (MAM) and a high of 38% for the short rains season (OND). As per Fig. 2, the normalized rainfall variability in the long rainfall season represents highest exposure in Naathu ward with 87%, and Nyiro ward for short rainfall season with represented high exposure of 75%. This was evident from the field questionnaires where most of the people agreed that there was a huge variability in season and late onsets of rainfall especially during the MAM rainfall season. This resulted to a lot of challenges for the community since they mainly rely on rainfall for their survival, because the majority of people depend on livestock keeping. Rainfall trend showed decreasing trends in some regions within the basin as observed in Fig. 2, where Ndoto ward had the high decreasing rainfall trend reflecting high exposure of 76% during the long rains season and 83% in the short rain season.

Sensitivity component analysis

See Figs. 5 and 6.

Landuse landcover change

The sensitivity component analysis was composed of six indicators, majorly environmental and socio-economic datasets. These data indicators included landuse landcover change, vegetation condition index, education level, human population, livestock population and poverty index. Landcover analysis was done as per Fig. 5, results for the landuse landcover map for 1986 shows that a lot of area in the northern Samburu had closed and open forests, the total area under closed forest being 780 km², while open forest covered a total area of 4807 km², this showed that the forests were less deforested due to lower population that could alter this type of landcover, hence preserving the river flows

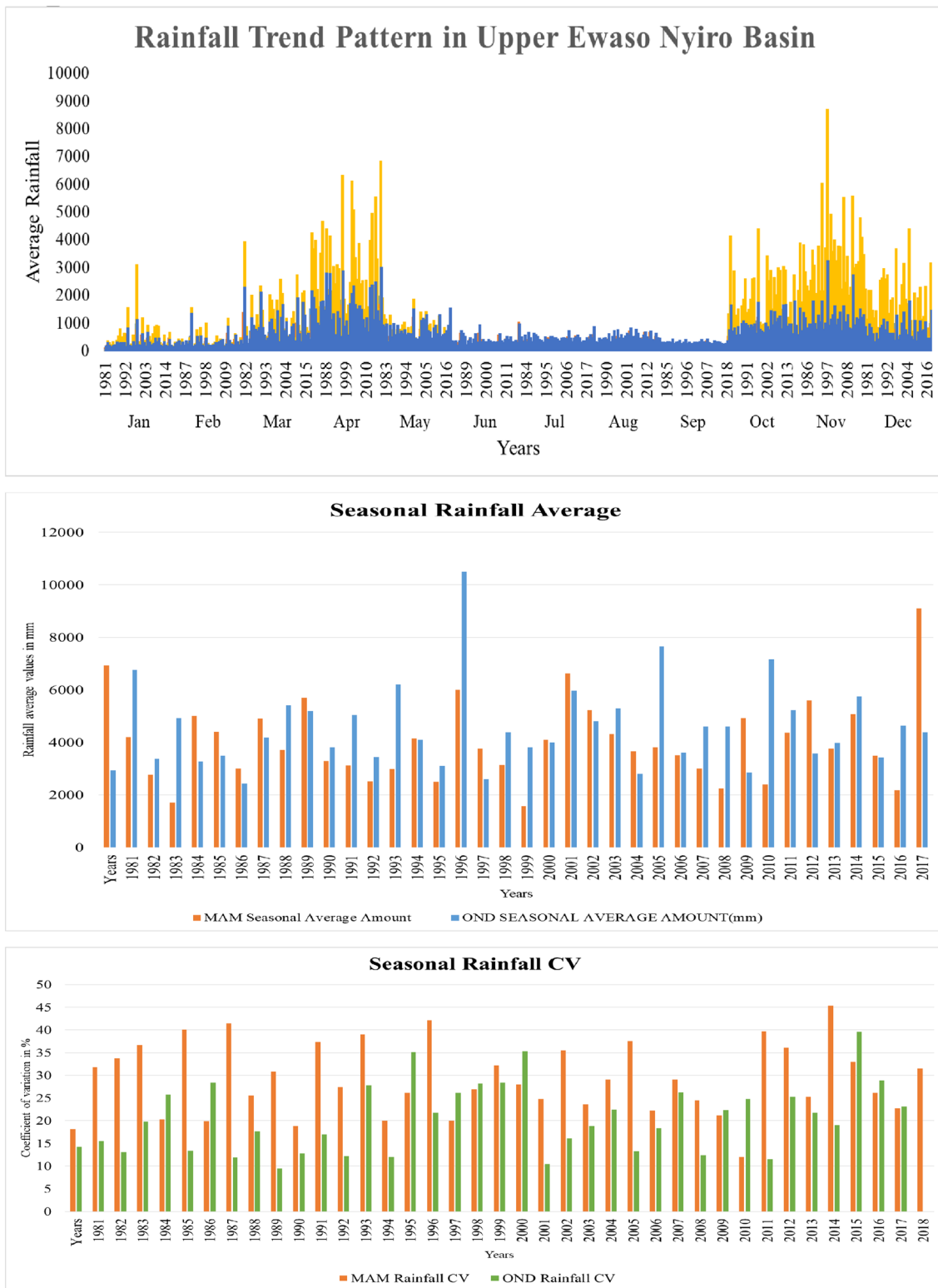


Fig. 3 Rainfall trend pattern in Upper Ewaso Nyiro basin

especially the Ewaso Nyiro river within this area. Waterbody areas in the year 1986 was relatively high at an area of 8.9 km² indicating that the communities within this area

were accessing water for their livestock and for domestic use and hence their sensitivity to climate change was minimal due to preserved landcover types. Shrubland area in the

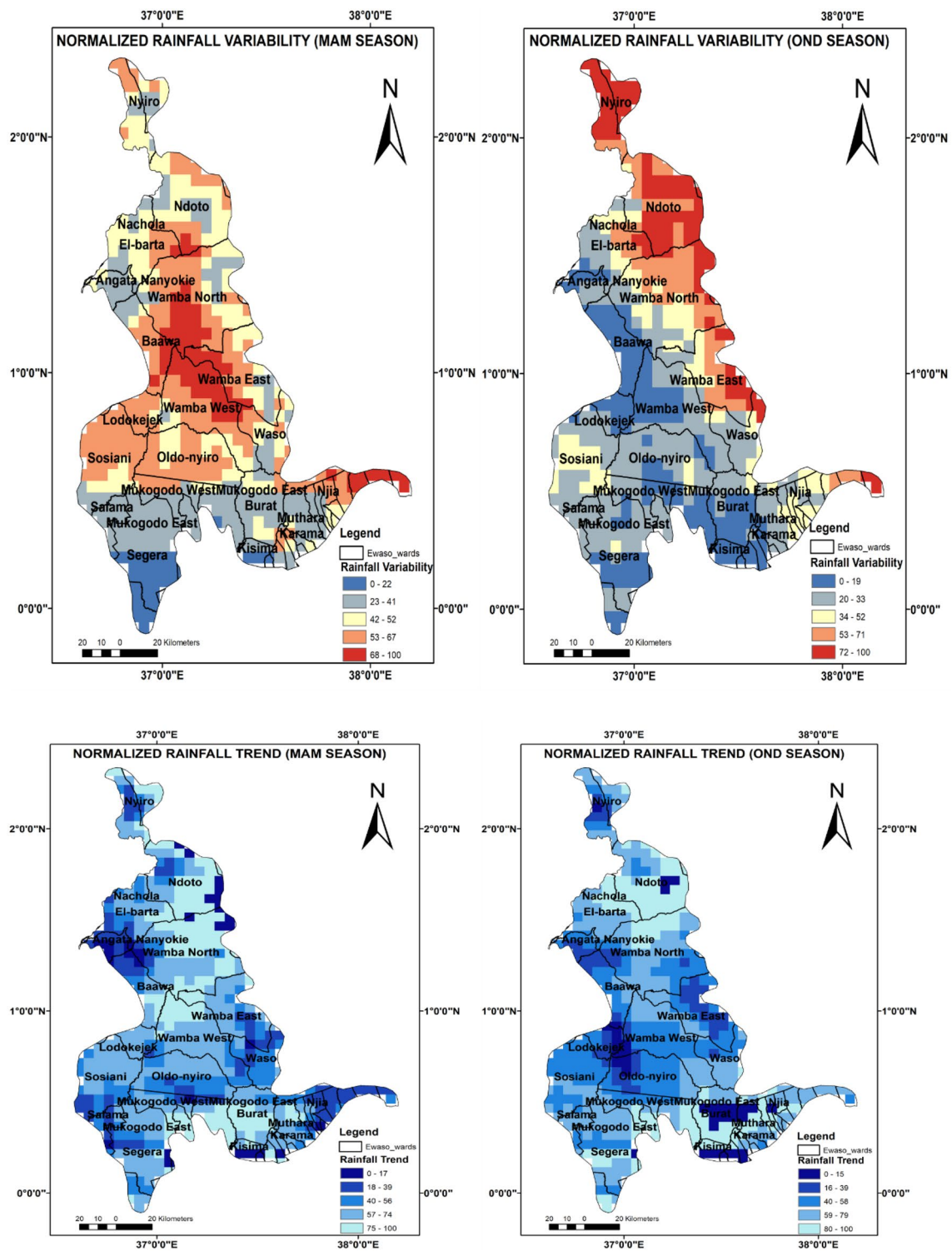


Fig. 4 Exposure layers

year 1986 was at 7442 km² this type of landcover is useful for the wildlife and livestock since it provides, this was the most dominant landcover class type. The 2018 landcover map indicates decrease in both the closed and open forests,

the closed forest shrunk by 197 km² while the open forest shrunk significantly by 2907.9 km². This showed how the changes over time had impacted on the forest system at large. The shrublands had increased by 3709.91 km² and

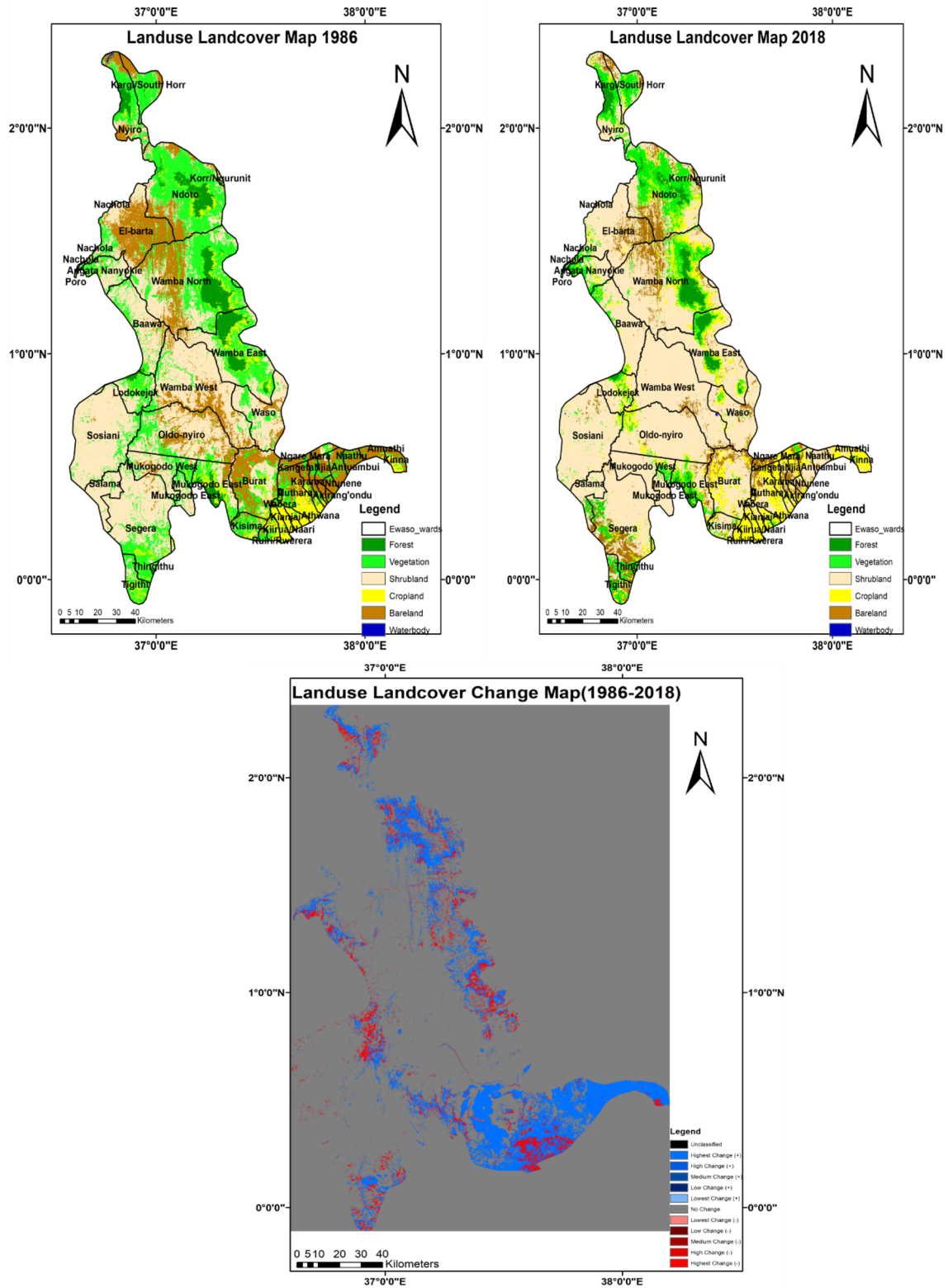


Fig. 5 Landcover change layers

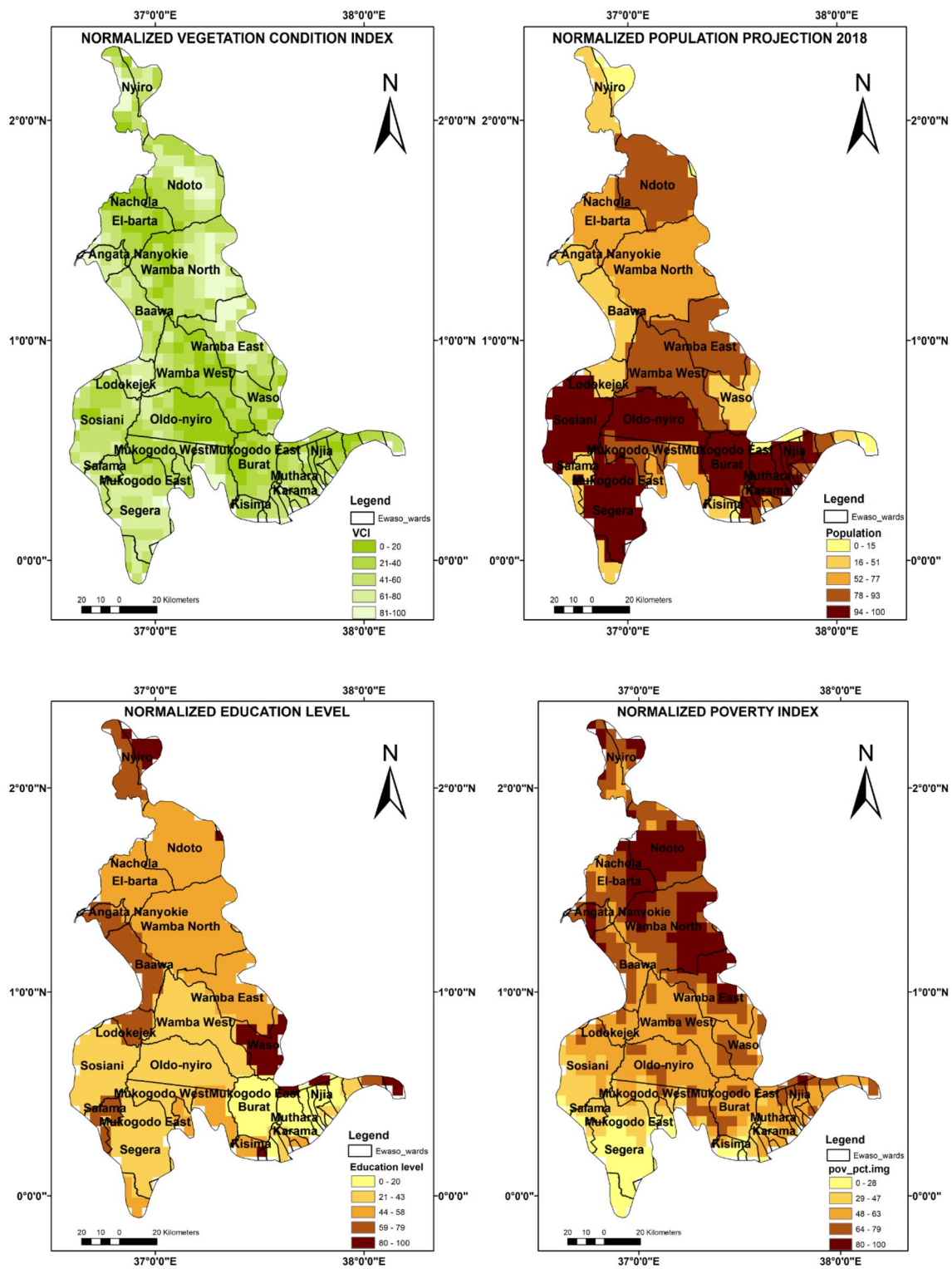


Fig. 6 Sensitivity layers

the cropland too increased by 1209.41 km², the population increase could be the reason for conversion of other land types to agricultural lands especially along the rivers and forests. Barelands reduced by 1749.96 km² and the

waterbody also reduced by 5.87 km² and this could be as a result of decrease in the forest areas within the catchment that is responsible for ground water flow regulation as well as abstraction of water for agricultural purposes (Table 2).

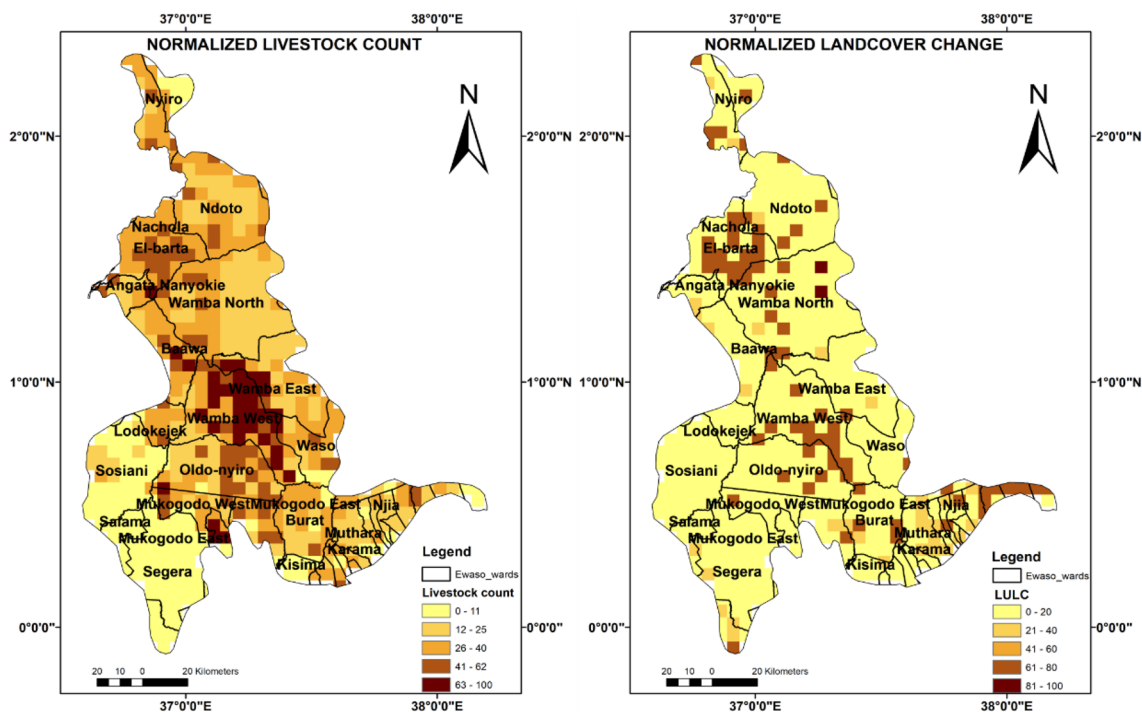


Fig. 6 (continued)

Table 2 Landuse landcover change statistics

| Landuse landcover types | 1986 | 1986 | 2018 | 2018 |
|-------------------------|-------------------------|----------|-------------------------|-------------|
| | Area (km ²) | Area (%) | Area (km ²) | Area (%) |
| Closed forest | 780.42 | 4.52 | 535.89 | 3.103447205 |
| Open forest | 4806.81 | 27.85 | 1898.93 | 10.9970273 |
| Shrubland | 7441.63 | 43.12 | 11,151.54 | 64.58053753 |
| Cropland | 1020.81 | 5.92 | 2230.22 | 12.91560231 |
| Bareland | 3198.08 | 18.53 | 1448.04 | 8.385869343 |
| Waterbody | 8.89 | 0.05 | 3.02 | 0.017516317 |

Vegetation condition index

The vegetation condition index communicated the current activity of the vegetation relative to the historical range (minimum and maximum NDVI values) calculated for the corresponding time from the long-term mean. Areas with a normalized low vegetation condition index has a high sensitivity to climate change, hence were parts of Isiolo (Oldo-nyiro) indicates low vegetation index hence high sensitivity of 75%, while high good normalized vegetation condition was observed in Samburu (Wamba North) with low sensitivity of 15%, as seen in Fig. 6a. This would mean that livestock had enough pasture in these areas and also the soil organic carbon was quite high, leading to

more exploration on farming practices since the soils are more fertile.

Population count

A high population was projected mostly in Laikipia county and Isiolo county and Meru North, resulting in high sensitivity, normalized high population indicates a higher sensitivity of 98% in Sosiani ward, Laikipia County as observed in Fig. 6a. A high population increase has a negative influence on the ecosystem since there would be more pressure on the available resources resulting to negative impacts for instance decrease in forests and increase in croplands and built up areas. A correlation on the landuse landcover change maps and projected population in areas such as

Meru County and Laikipia showed a significant correlation in areas of high population and landcover change from forests to cropland.

Education level

Low education level was highest in Samburu County, where Waso ward had the lowest education level indicating high sensitivity of 89%, while the most educated ward was observed in Kangete, Meru county demonstrating low sensitivity. Education level a role in vulnerability assessments since a community that is highly educated is more aware and informed on current matters and will be more likely to understand climate change impacts and adaptive more efficiently to its impacts. Education level is an added advantage, subsequently one is able to get good jobs with a better education and therefore as a results earns salary and hence improve their standard of living, diversifying sources of income and less reliance on livestock keeping.

Poverty index

High poverty level was quite high throughout the area of study, especially in Samburu and Marsabit county, while low poverty levels were observed in Laikipia and Meru County. Ndotu ward in Samburu in Fig. 6a observes a high poverty level hence resulting in high sensitivity of 91%. Poverty level

plays a significant role in the sensitivity of the population to climate change impacts since populations that have a poverty level are more likely to be impacted by issues of climate change, because they lack the capacity and resources that would enable them to bounce back after a climatic shock. These areas with high poverty are more sensitive to climate change and hence more vulnerable to climate change.

Livestock count

High livestock population was observed in Samburu and Isiolo region as per Fig. 6b. A high sensitivity of 84% is observed in Wamba west Samburu County due to high livestock counts recorded in this region. High livestock indicate high sensitivity to climate change, because more livestock are likely to be affected by climate change impacts like droughts and diseases, high completion over the available scarce resources might occur hence depleting resources. Alternately, a pastoralist with high numbers of livestock count would mean a lower poverty level, since his/her wealth is determined by the number of livestock.

Lack of adaptive capacity component analysis

See Fig. 7.

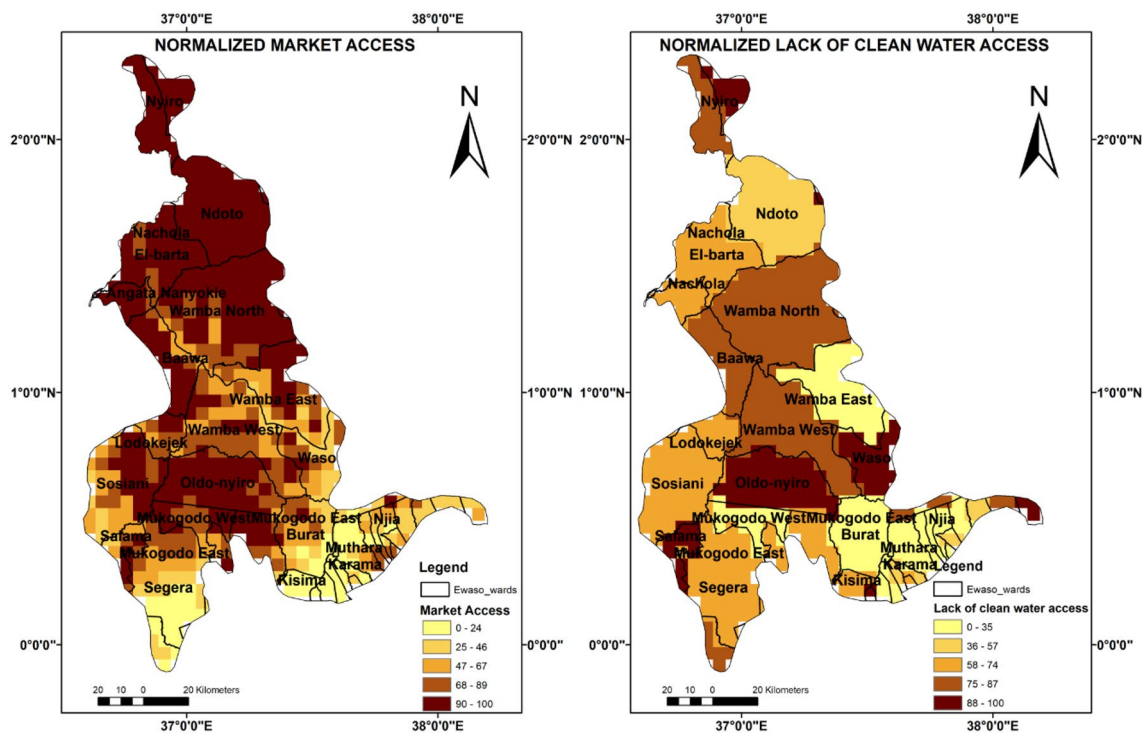


Fig. 7 Lack of adaptive capacity layers

Access to clean water

Samburu and parts of Isiolo, Marsabit and Laikipia were observed to experience challenges in accessing clean water from different water sources according to Fig. 7. Waso was affected by challenges of clean water access hence leading to high lack of adaptive capacity of 93%. Majority of populations in Meru County had improved water access for domestic use. Access to clean water is a crucial factor since it plays a big role in the health of human and livestock populations. Poor health conditions results in low productivity and hence the economy of a county would be affected, resulting in high vulnerability.

Market access

Market access map indicates the approximate time taken by an individual to access a market, the longer the time taken to access the market the higher vulnerability. Ndoto ward has the biggest challenge in accessing markets as per Fig. 7, this results to high lack of adaptive capacity of 96%. Hospitals, schools, livestock markets and shops are found in market centres, which is important for communities. The more time one takes to get to the market would mean several possibilities, i.e. poor roads, few market centres within the area, poor public transport, etc. Many areas across the basin were observed to take more than 2 h to access markets, resulting in high vulnerability.

Modelling vulnerability index

See Figs. 8 and 9.

Exposure index

The exposure map in Fig. 8 was developed to show which ward were highly exposed to climate hazards. According to the exposure map El-barta ward, Wamba West, Wamba North, Naathu, Amuathi and Korr wards were highly exposed. The highest ward exposed was Amuathi ward with 71%. Regions with high decline and variability in rainfall mainly contributed to high exposure. High temperature trends showed an increase in temperature that results in increased evaporation rates leading to drying up of rivers, pasture and crops causing increased drought situations.

Overall, the analysis undertaken within the exposure component gives us a glimpse of the climate dynamics that the community is exposed to over time and, therefore, bringing the sensitivity and lack of adaptive capacity allows us to analyse the vulnerability of the community within the context of climate change.

Sensitivity index

The most sensitive areas were located in Samburu County. All indicators seemed to influence sensitivity in several locations in various ways. Naathu ward was highly sensitive with 78% as observed in Fig. 8, this could be as a result of its high population, landcover change and relatively high poverty level in Naath ward. The landcover analysis indicated that a lot of dense vegetation and forest cover had converted to farm lands, hence affecting the micro-climate (Table 3).

Lack of adaptive index

Lack of adaptive capacity component was a composite of access to clean water and access to markets datasets. These datasets were few due to the limited availability of socio-economic datasets. Using the available datasets for analysis, the adaptive capacity was lowest in Korr ward, with 100% as per Fig. 8. The population in Korr are trapped in a cycle of challenges the main one being lack of access to clean water. It is known widely that the county of Marsabit has challenges regards to clean water accessibility for human and livestock and this is worsened by the frequent droughts experienced from time to time. The resilience of a household to climate-related shocks is influenced by the adaptive and coping capacity as much as it is by the magnitude of these shocks or stressors (Choularton et al. 2015). Results in Fig. 8 showed that a larger region across the study area lacked sufficient capacities to adapt. Communities with weak socio-economic capitals would be impacted more by the negative impacts of climate change We used the term “lack of adaptive capacity” term instead of “adaptive capacity” for purposes of creating a linear relationship of the component to vulnerability, meaning a high lack of adaptive score means high vulnerability and a low lack of adaptive capacity score means a low vulnerability. All components have a linear relationship to vulnerability (Table 4).

Overall vulnerability index mapping

Vulnerability index was developed using the equal weighted averaging approach to derive a single index that communicates vulnerability (Table 5).

Overall community climate vulnerability highlighted hotspot areas that require interventions to build their resilience. These are the areas that scored highly for vulnerability; Samburu County, Marsabit county and Isiolo County. Amuathi, El-barta, Kargi/South Korr, Kinna, Naathu, Kinna, Ndoto, Nyiro, Oldo-nyiro, Wamba North, Wamba West and Korr. These vulnerable areas had high exposure, sensitivity and lack of adaptive capacity scores that results in obviously high vulnerability. The highest vulnerability was observed in Korr/Ngurunit ward in Marsabit County. Approximately,

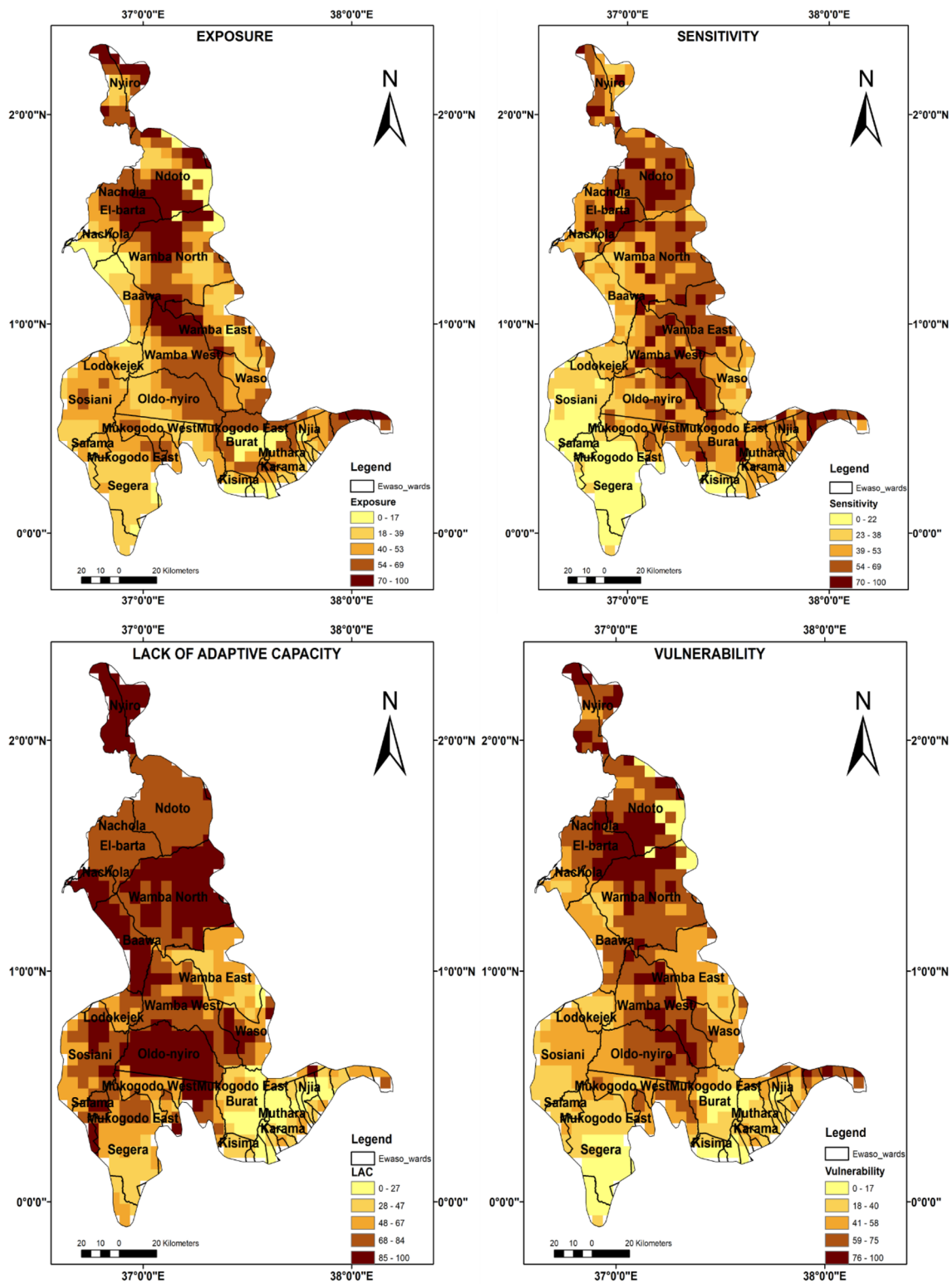


Fig. 8 Exposure, sensitivity, lack of adaptive capacity and overall vulnerability layers

45.45% of the population was observed to be highly vulnerable to climate change impacts, while 54.55% of the

population was noted to be moderately vulnerable to climate change impacts. A resilience planner could thus decide to

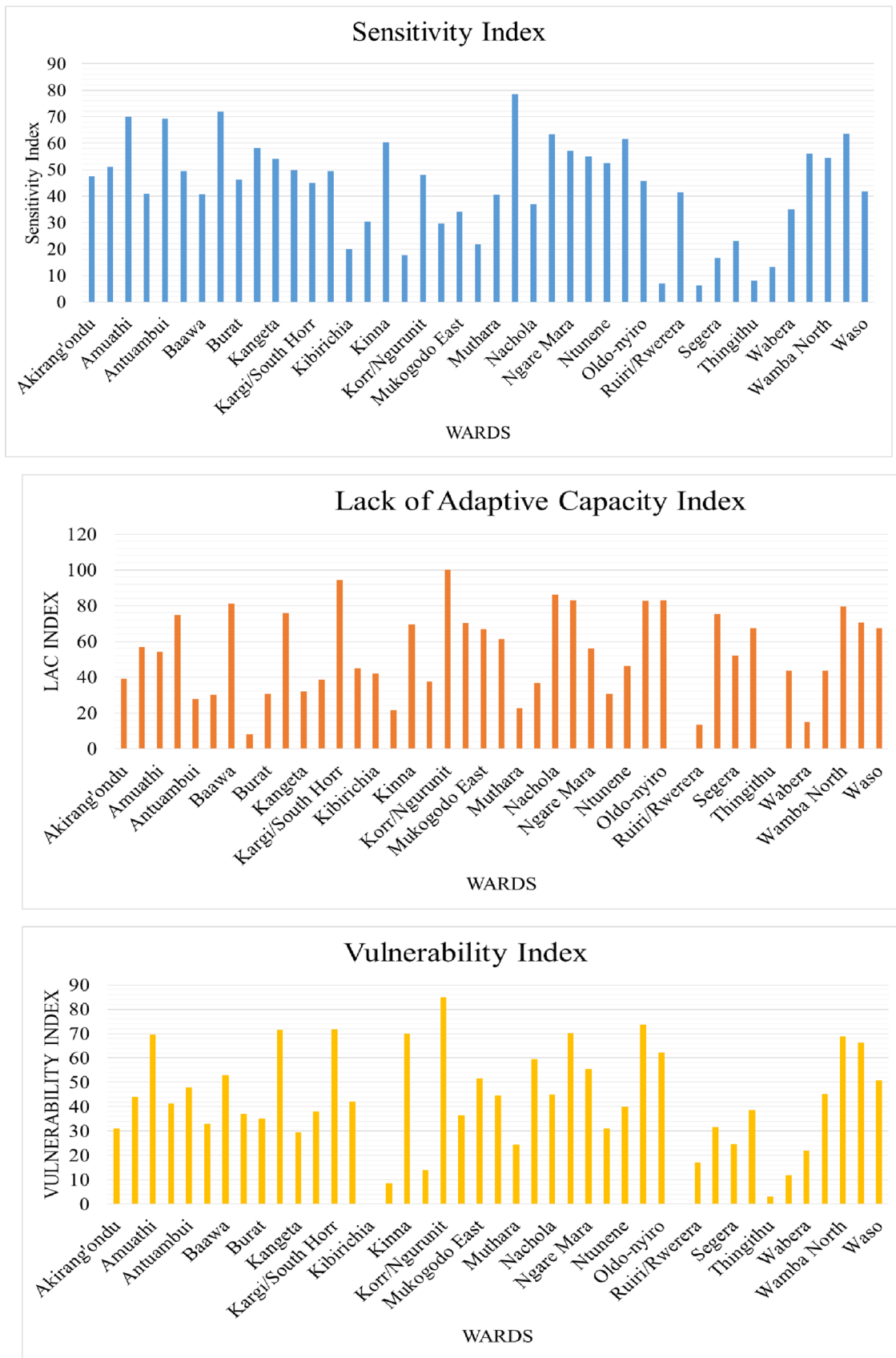


Fig. 9 Graphs representation of sensitivity index, lack of adaptive capacity index and overall vulnerability index

Table 3 Sensitivity categories in the various wards

| Natural breaks | Sensitivity index category | Wards |
|----------------|----------------------------|--|
| 0–18 | Lowest | Kisima, Poro, Segera, Thingithu, Tigithi |
| 18–40 | Low | Kibirichia, Kiirua/Naari, Lodokejek, Mukogodo East, Mukogodo West, Nachola, Sosiani, Wabera |
| 40–57 | Medium | Akirang’onde, Akithi, Angata Nanyokie, Athwana, Baawa, Burat, Kangeta, Karama, Kargi/South-Horr, Kianjai, Korr/Ngurunit, Muthara, Njia, Ntunene, Oldo-nyiro, Ruiiri/Rwerera, Wamba East, Wamba North, Waso |
| 57–75 | High | Amuathi, Antuambui, BullaPesa, El-barta, Kinna, Naathu, Ndoto, Ngare Mara, Nyiro, Wamba West |
| 75–100 | Highest | Naathu |

Table 4 Lack of adaptive capacity categories in the various wards

| Natural breaks | Lack of adaptive capacity index category | Wards |
|----------------|--|--|
| 0–18 | Lowest | Bulla Pesa, Ruiiri/Rwerera, Wabera |
| 18–40 | Low | Akirang’onde, Antuambui, Athwana, Burat, Kangeta, Karama, Kiirua/Naari, Kisima, Muthara, Naathu, Njia, Thingithu |
| 40–57 | Medium | Akithi, Amuathi, Kianjai, Kibirichia, Ngare Mara, Ntunene, Segera, Tigithi, Wamba East |
| 57–75 | High | AngataNanyokie, Baawa, Lodokejek, Mukogodo East, MukogodoWest, Salama, Sosiani, Wamba West, Waso |
| 75–100 | Highest | El-barta, Kargi/South Horr, Korr/Ngurunit, Nachola, Ndoto, Nyiro, Oldo-nyiro, Wamba North |

Table 5 Vulnerability categories in the various wards

| Natural breaks | Vulnerability index category | Wards |
|----------------|------------------------------|---|
| 0–18 | lowest | Kibirichia, Kiirua/Naari, Kisima, Ruiiri/Rwerera, Thingithu, Tigithi |
| 18–40 | Low | Akirang’onde, BullaPesa, Burat, Kangeta, Lodokejek, Muthara, Njia, Salama, Segera, Sosiani, Wabera |
| 40–57 | Medium | Akithi, AngataNanyokie, Antuambui, Baawa, Karama, Kianjai, Mukogodo, East, MukogodoWest, Nachola, Ngare Mara, Ntunene, Wamba East, Wamba West |
| 57–75 | High | Amuathi, El-barta, Kargi/South Korr, Kinna, Naathu, Kinna, Ndoto, Nyiro, Oldo-nyiro, Wamba North, Wamba West |
| 75–100 | Highest | Korr/Ngurunit |

Table 6 Estimated population in each vulnerability category in the entire basin

| Natural breaks | Vulnerability index category | Population count |
|----------------|------------------------------|------------------|
| 0–18 | Lowest | 80,218 |
| 18–40 | Low | 345,569 |
| 40–57 | Medium | 207,620 |
| 57–75 | High | 147,032 |
| 75–100 | Highest | 142 |

target this group of people for interventions to build their resilience while ensuring that resilience building activities in the other 54.55% of the population are sustained to mitigate

chances of this group falling under high vulnerability categories (Table 6).

Identification of suitable adaptation measures

The respondents provided suggestions to suitable adaptation plans that could help improve their livelihoods and adjust to the shocks of climate change. It was observed that various adaptation strategies were useful to them but of importance adaptation measures were livestock offtakes before droughts to minimize loss, organized grazing plans and improved access to markets and market information. These tops as their priorities and therefore the government and local organizations needs to provide capacity and prioritize efforts and activities to achieve the above coping strategies.

Table 7 Adaptation strategies in order of importance

| Adaptation strategies | Very important (%) | Important (%) | Mod-erately (%) | Low (%) | Not necessary (%) |
|---|--------------------|---------------|-----------------|---------|-------------------|
| Livestock offtakes before droughts to minimize losses | 72 | 20 | 8 | | |
| Comprehensive grazing plans; covering the conservancies and neighbouring communities | 68 | 30 | 2 | | |
| Enhance access to markets and market information particularly for livestock | 56 | 16 | 12 | 16 | |
| Diversification of livelihoods including promotion of emerging | 33 | 9 | 2 | 30 | 26 |
| Enhance water availability and access through water harvesting initiatives | 53 | 21 | 26 | | |
| Routine disease surveillance, treatment and vaccination programs | 57 | 33 | 30 | 30 | |
| Promotion of livestock insurance(Index-based livestock insurance) programs | 30 | 18 | 24 | 19 | 9 |
| Access and use of climate information for informed decision making on livelihoods and disaster risk reduction (DRR) | 25 | 39 | 21 | 17 | 8 |
| Migration in search of pasture | 12 | 3 | 7 | 30 | 48 |
| Improvement of health care facilities | 48 | 36 | 14 | 2 | |

New emerging trends and technologies for livestock keeping practices were also desired by farmers.

Water availability is very crucial since the livestock depend on water for survival, therefore, more boreholes, dam, water pans and taps needs to be constructed and residents should also be educated on water harvesting techniques and initiatives.

These areas need interventions and resilience building to uplift the livelihood status in a sustainable manner. Focusing this study at local (ward) level aims to guide stakeholders to provide sustainable interventions and efforts to communities at local level for more effective results and visible impacts (Table 7).

Conclusion and recommendation

Conclusion

The Upper Ewaso Nyiro basin is a key ecosystem to Kenya since it provides a wide range of ecosystem services and is home to wildlife, livestock population and most importantly it is a significant water catchment area. There exists challenges within the basin that relates to climate change, increasing human pressure, unsustainable landuse practices, and declining wildlife ranges. Consequently, this study leveraged on climate change to understand the vulnerability of the community using a GIS modelling approach.

To assess climate vulnerability of communities in the ASALs area of Upper Ewaso Nyiro basin to climate change, it was necessary to select various data indicators that were proxies representing the components being measured (exposure to climate change, sensitivity of the social community system and the adaptive capacity or coping capacity of the community). The framework followed a detailed

vulnerability assessment methodology by International Panel on Climate Change vulnerability components: Exposure, Sensitivity and Adaptive capacity.

The results from the exposure component analysis showed that there has been high climate variability over 30 years especially within the long rains in March, April and May. The exposure layer generated from the climate stressors highlighted that Samburu county was highly exposed to the climate stressors, with high values seen in El-barta ward. Sensitivity analysis aggregated a couple of datasets that was used to depict how sensitive these areas are to climate change. The indicators selected were environmental and livelihood data. The sensitivity index showed Samburu County had many wards that were highly sensitive, followed by Meru and Isiolo County. The sensitivity index was an interplay of multiple factors such as a high landcover changes from forest cover to croplands which resulted to a high sensitivity index, this together with poverty level, education level and vegetation index plays a big role in the overall sensitivity index and hence the important players should provide sustainability programs that will help improve the sensitivity of a community to climate change.

Lack of adaptive capacity was high in areas such as Marsabit and Samburu County and, therefore, efforts should be directed to improve the coping strategies and enhance resilience of these communities within the named counties. It was important to analyse the three components separately since it will enable decision makers understand and single out underlying factors that contribute to overall vulnerability.

Modelling climate vulnerability followed the IPCC framework methodology and used an additive approach for all the components and then followed by averaging. The additive approach assumes a linear relationship between input layers and the conceptual category being measured.

It also assumes that good levels for one component (e.g., high adaptive capacity) compensate for bad levels in another (e.g., high exposure and sensitivity) but this might not necessarily be the case. In some cases, the interaction of these could be multiplicative.

Our analysis identified wards most likely to be more vulnerable to climate stressors. The county that has the highest number of wards with high vulnerability was from Samburu County. The vulnerability scores is a single index that provides meaningful information to decision makers, conservation managers, local and county government, since the maps provide spatial information that aids in easy communication concerning the situation on the ground for targeted efforts.

Suitable adaptation strategies was discussed and it was suggested that priority should be given to livestock market systems, water availability, grazing plans and routine surveillance, treatment and vaccination programs, although this region has received increased attention with the aim of strengthening resilience support systems such as expanding social safety nets, the importance of sustaining resilience efforts cannot be over emphasized, since this will strengthen coping capacities so as to improve the livelihoods of the people.

Recommendation

Accordingly, the study showed that vulnerability of the community within Upper Ewaso Nyiro basin to climate change has been worsened because of the complex interactions and interrelations among these components.

Based on the results, the study recommended the following:

Climate change and ASAL management policies

The study has done an assessment and provided information on vulnerability index and based on these results, the government and policy makers needs to use this information to come up with sustainable, realistic and effective policies mainly in the area of rangeland and ASAL management practices linking to the climate vulnerability results this research provides.

Improvement of early warning systems

With experienced increase in climate change impacts, it is important for the Kenya Meteorological services to provide timely information on climate and weather especially during drought, delaying rainfall and flood events. There should be a consistent early warning system in place for example message alerts that is received even in the very

remote areas. This is important since it will provide awareness and allow for preparedness by an individual.

Promotion of efficient livestock market systems

This is a key component, most of the people depend on livestock as their main source of livelihoods, and therefore markets systems is very crucial. The community requires an effective market system whereby the markets are easily accessible, the location suitable where it attracts demands for the livestock, and the prices for offtake of livestock should be lucrative. This will promote the livestock owner and will be able to gain from pastoralism.

Collaboration between the national government, County government, local organizations and the private sector in provision of basic amenities in the Upper Ewaso Nyiro

Provision of basic amenities, social safety nets, employment opportunities is dependent on a collaborative initiative by all relevant stakeholders to provide solutions to development initiatives within this region. To achieve success this collaboration is paramount, since if a region has good hospitals, good roads, water availability, schools, etc. then, it will be able to definitely lower the vulnerability of a population.

There is need for further research to have a more in-depth understanding of vulnerability and adaptation of pastoralists to climate change in Ewaso Nyiro Basin. This study suggested the following areas for future research:

1. Sector-based vulnerability assessment within Ewaso Nyiro basin with a focus on the water sector.
2. Incorporation of the 2019 Kenya population counts into the vulnerability analysis based on the upcoming census data.
3. Simulating the interaction of poverty in climate vulnerability based on future climate scenarios.

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