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Supplementary Material - Mapping vulnerability to multiple hazards in the Savanna Ecosystem in Ghana

1 Introduction

This supplementary material describes the data, sources and rasterisation and presents a map of the evaluation exercise. The primary data were collected through questionnaire survey, focus group discussions and in-depth interviews. In determining the sample size (N), the formula $N = \frac{z^2 * \beta * (1-\beta)}{d^2}$, where z is the critical value at the chosen level of significance[1], β is the statistical power of the study and d is the margin of random error (also called confidence interval or size effect), was used (Fox et al., 2007). The conventional values for the level of significance at α=5% (i.e. 1.96) and a power of 80% at a margin of error of ±5% (Fox et al., 2007) were used, and this resulted in a sample size of 246. This number was broken down into 210 for household survey and 36 for institutional survey. The household sample was distributed as in Table S1.

Table S1 Distribution of household questionnaire

Bawku Municipal	Urban	Bawku	20
Bawku West	Rural	Kubore	15
Binduri	Rural	Kumpalgoga	15
Bolgatanga Municipal	Urban	Bolgatanga	25
Bongo	Rural	Bongo	15
Builsa North	Rural	Sandema	15
Builsa South	Rural	Fumbisi	15
Garu-Tempane	Rural	Tempane	15
Kasena-Nankana East	Urban	Navrongo	15
Kasena-Nankana West	Rural	Kayoro	15
Nabdam	Rural	Nagodi	15
Pusiga	Rural	Koose	15
Talensi	Rural	Pwalugu	15
Total			210

Source (Authors)

[1] Level of significance accounts for the type I error while the statistical power accounts for the type II error, i.e., the level and power at which we are prepared to accept these errors. Refer to Fox et al., 2007 for more detail.

The distribution of the sample was arbitrary with the urban towns given higher numbers based on the function of the town (regional, municipal or district capital). This decision was taken because at the time of data collection, population data which could have been used to determine the sample size of each town/village was unavailable.

Before vulnerability can be mapped, the data has to be converted into geographic layers by georeferencing. After georeferencing, all datasets were converted into raster layers since spatial analysis operations are best performed in raster format (see Damm, 2010). The conception of vulnerability was that it is the aggregate sum of susceptibility and adaptive capacity (see Section 2.4, page 8, in the body of the paper) and therefore the layers were aggregated at two levels, first to obtain susceptibility and adaptive capacity composite indices, and second, to obtain vulnerability indices (Fig. S1).

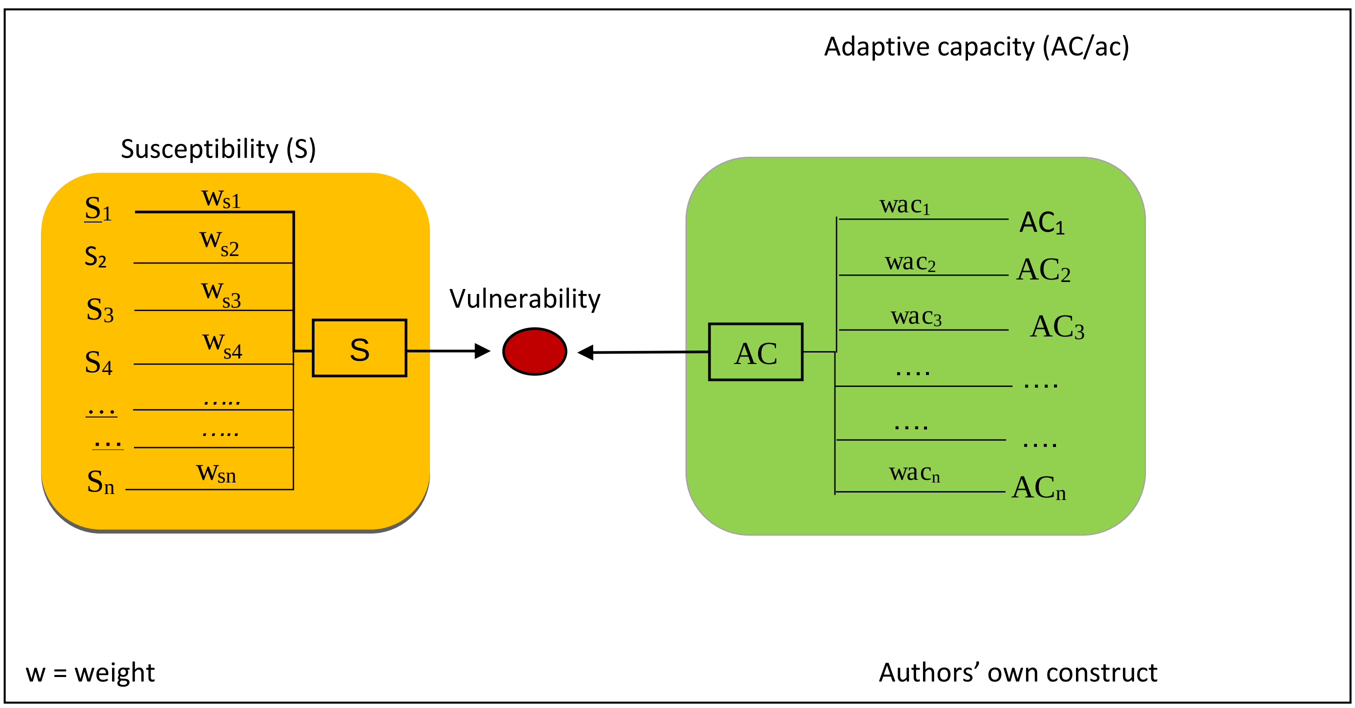

Fig. S1 Diagrammatical representation of vulnerability mapping

2 Development of susceptibility layers

This component of the analysis gathered all the indicators of exposure and sensitivity into geographic layers called susceptibility layers for each hazard for the various sectors. Other studies have used similar procedures to identify indicators and have combined them in this way (e.g. Kienberger et al., 2009; Damm, 2010). Susceptibility measures the degree to which systems/livelihood activities are adversely affected by hazards. The different livelihood activities identified are susceptible to different hazards, as these are located at different places over space and take place at different times. Thus, to practically implement the concept of susceptibility requires the categorisation of livelihood activities into a series of components related to sectors of the economy that are affected by the hazard in question, as proposed by Villagrán (2006, cited in Kienberger et al., 2009).

2.1 Susceptibility to drought/high temperatures layers

The people affected by drought/high temperatures engage in livelihood activities such as crop production and livestock farming, and key variables also include human population, health and water availability. The indicators that made each sector vulnerable to drought/high temperatures were identified and mapped as described below.

2.1.1 Agriculture

The agriculture sector is susceptible to events of droughts/high temperatures. Droughts result in crop failure and death of animals due to scarcity of water and fodder. The crop failure index was calculated using crop yield data from MOFA between 1992 and 2012. Yields of five major crops (maize, rice, sorghum, millet and groundnuts) were detrended using auto-regression (implemented in Excel) to predict yields with a 3-year lag (after Simelton et al., 2009). Predicted yields were obtained after removing the short-term effects of technology and other factors by detrending, and therefore any production loss could be attributed to climatic hazards (Simelton et al., 2009). The crop sensitivity index was derived from the crop failure index by dividing the predicted (or expected) yield by the actual yield (i.e. crop failure index = expected yield/actual yield) for each crop in each district. In order to characterise the sensitivity of the crops, a score between 1 and 1.49 was categorised as sensitive, 1.5 to 1.99 very sensitive and 2 or above as extremely sensitive. These categories were assigned values of 1, 2 and 3 respectively. Water Holding Capacity (WHC) of the soil types in the region obtained from Amegashie (2009) serves as the impact of the hazards on the soil. Pasture availability for animals was calculated from grasslands using 2010 Aster satellite imagery. The maps for the agricultural sector susceptibility are shown in Fig. S2.

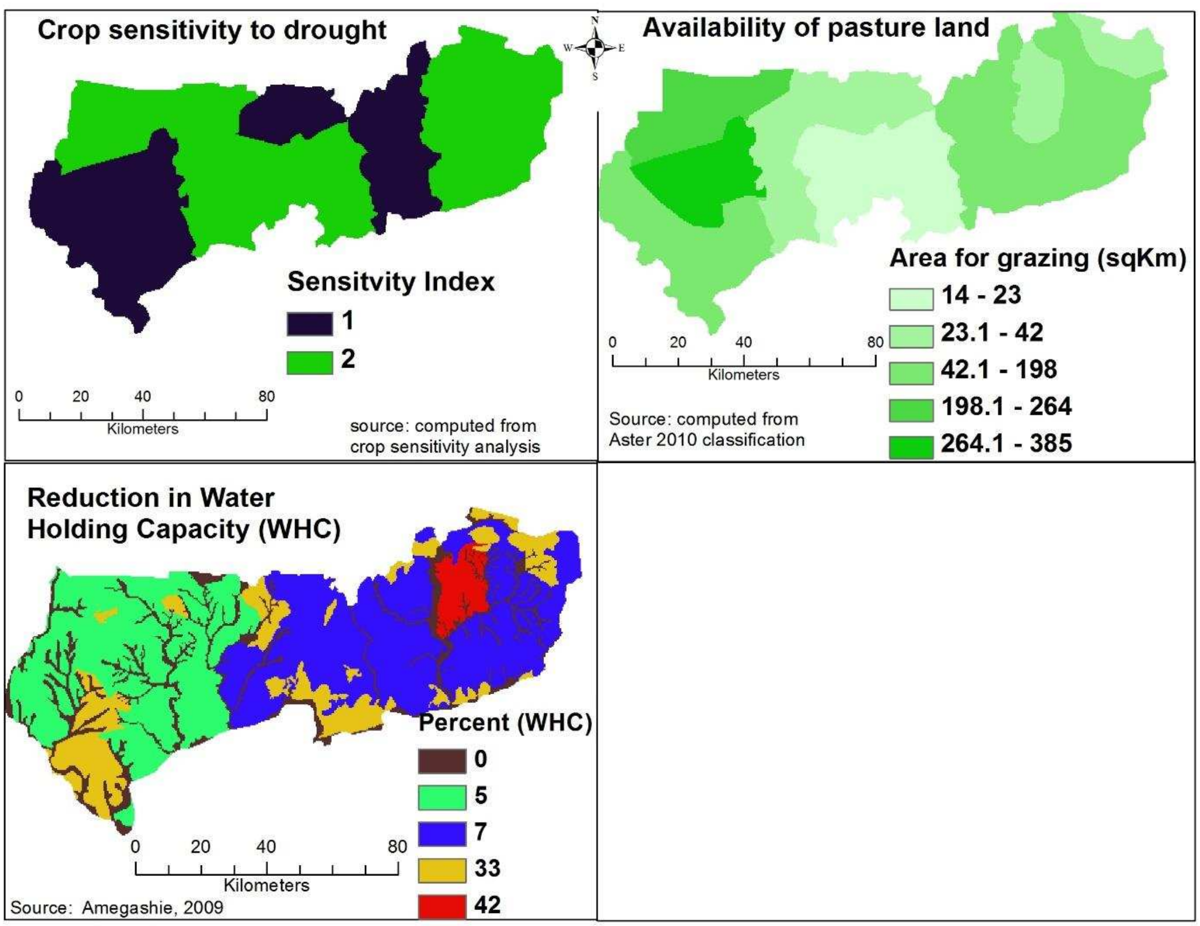

Fig. S2 Susceptibility of agriculture to drought/high temperatures

2.1.2 Health

Drought/temperature affect the population in several ways but most importantly, they can lead to food shortages and bring about illnesses such as cerebrospinal meningitis (CSM) and malnutrition, as well as a reduction in income. The food shortage component was determined using food insecurity status at district scale, obtained from the World Food Programme (WFP, 2012) report. This dataset also served as a proxy for malnutrition since it was difficult to obtain any other data on malnutrition. This dataset was linked to the district shapefiles in ArcGIS 10.2 and used to map the food insecurity indicator. Drought affects the entire population but its largest impact is on the rural population. Therefore, the distribution of the population was mapped according to whether the area was urban or rural. This data was obtained from the 2010 population and housing census which delimits rural and urban populations. It was assumed that districts with higher rural populations will be more susceptible to food crises due to droughts than those with lower rural populations. Households engaged in agriculture were considered more susceptible to droughts than those not involved in agriculture as they suffered from reduced income whenever drought occurred. Thus, the number of households involved in agriculture in each district was considered in mapping susceptibility to drought. This data was also obtained from the census report. Districts with a higher number of households in agriculture were considered more susceptible than those with lower households.

CSM case fatality rates for the various districts were used to map the CSM indicator. This data was obtained from the regional health report (Ghana Health Service, 2012). Fatality rates show the degree of susceptibility of the districts to CSM in terms of lives lost per reported case. Therefore, districts with higher case fatalities were considered more susceptible to high temperatures (i.e. heat). These indicator layers are shown in Fig. S3.

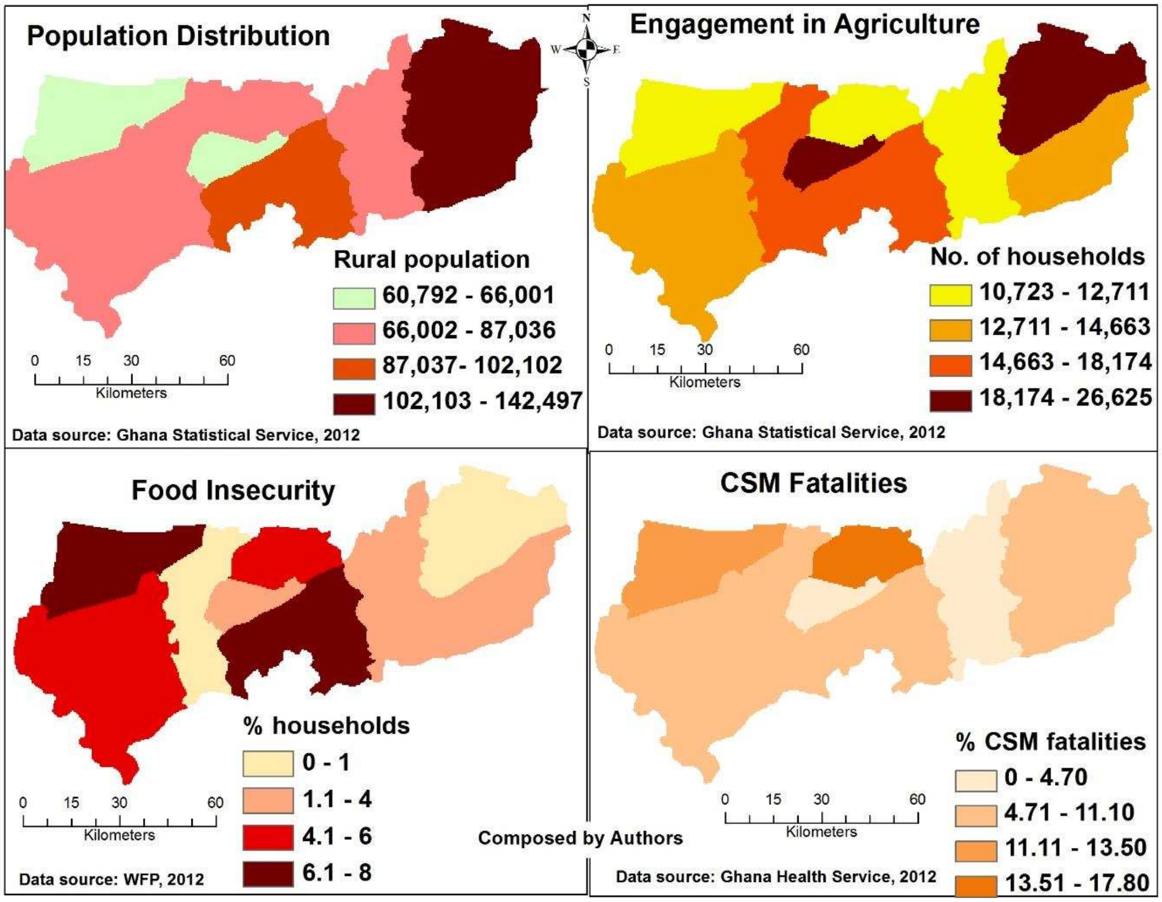

Fig. S3 Susceptibility of humans to drought/high temperatures

2.1.3 Water sector

When there is drought or high temperatures, surface water bodies dry up while ground water recharge reduces. For surface water, the number of reservoirs per district was counted and used to map susceptibility to droughts/high temperatures. The assumption is that a district with a higher number of reservoirs will be less susceptible than one with a lower number, because it may still have some reservoirs with water and less crowding of animals and humans at the remaining few water points. A similar approach was used by Kienberger et al. (2009) where they took the number of spring water bodies to indicate susceptibility to floods. Data used in the present study was obtained from the IDA (2013) in Excel format. Numbers were cross-checked with the dams identified on Google Earth in 2013 and linked to the district boundaries as some districts were divided after the 2010 population and housing census. Groundwater susceptibility was mapped using the recharge map produced by Obuobie (2008). This map showed the ranges of ground water recharges interpolated over the region. The map was exported as a .jpeg file, georeferenced and digitised. Places with low recharge were considered more susceptible to droughts/high temperatures than those with high recharge rates. This is because the region depends on groundwater for nearly all its domestic water requirements and some dry season gardening. These susceptibility layers are shown in Fig. S4.

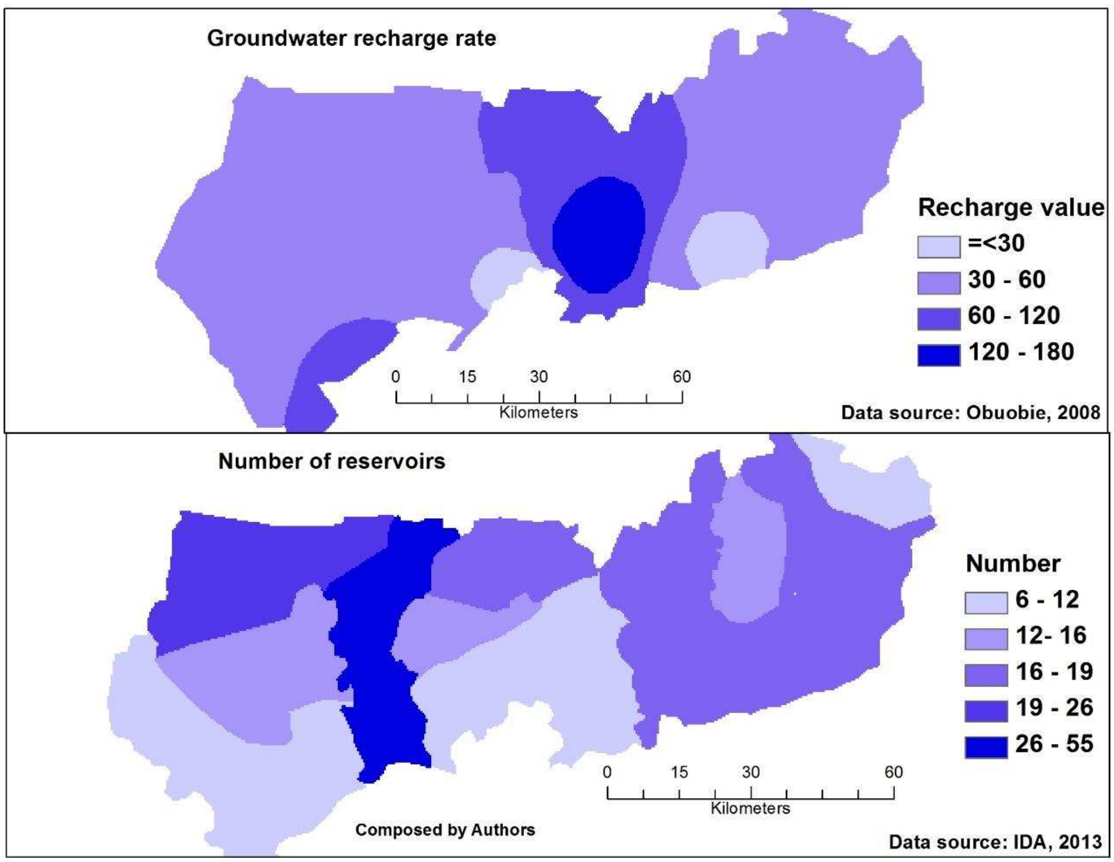

Fig. S4 Susceptibility of water sector to drought/high temperatures

2.2 Susceptibility to floods/high precipitation layers

Floods and/or high rainfall impact heavily on the livelihood activities of the people in the region. Impacts range from crop failure, erosion of soil through to health problems and siltation of water bodies. The datasets required to map the susceptibility layers are described according to the main livelihoods, based on data availability.

2.2.1 Agriculture

The average crop failure index of 2010 (see body of the paper, Section 2.2) was used to map the crop susceptibility to floods/heavy rainfall. This indicator was used because it is the net effect of the destruction of farms by floods and the frequent heavy rains that may prevent proper pollination of crops (Derbile and Kasei, 2012). Agriculture also suffers from flooding as the soil is eroded. Thus, the erosion component was determined from a proxy. Halm and Asiamah (1984) surveyed and mapped the types of erosion occurring in the region based on the characteristics and properties of the soils. This map was digitised and used as a proxy. Erosion is determined by the properties and exposure of the soil, the land cover type and slope. These factors were considered by Halm and Asiamah (1984) in their survey. The erosion map (Fig. S5) showed areas that were affected by normal erosion, areas affected by moderate sheet erosion, severe sheet and gully erosion and those affected by very severe erosion. These categories were confirmed by farmers to be occurring in the towns/villages. Some of the areas were visited and their GPS coordinates coincided with the map. The categories were rated 1, 2, 3 and 4 respectively using the categorical scale method (see Nardo et al., 2005).

Erosion leads to nutrient and soil losses. Eroded soils are carried into water courses and dams/dugouts, silting them up and reducing their capacity. Therefore, soil loss was used as a proxy to estimate siltation of waterbodies/courses with the assumption that all the eroded soils will be deposited in the waterbodies. Amegashie (2009) sampled soils in the region and determined soil and nutrient losses due to erosion.

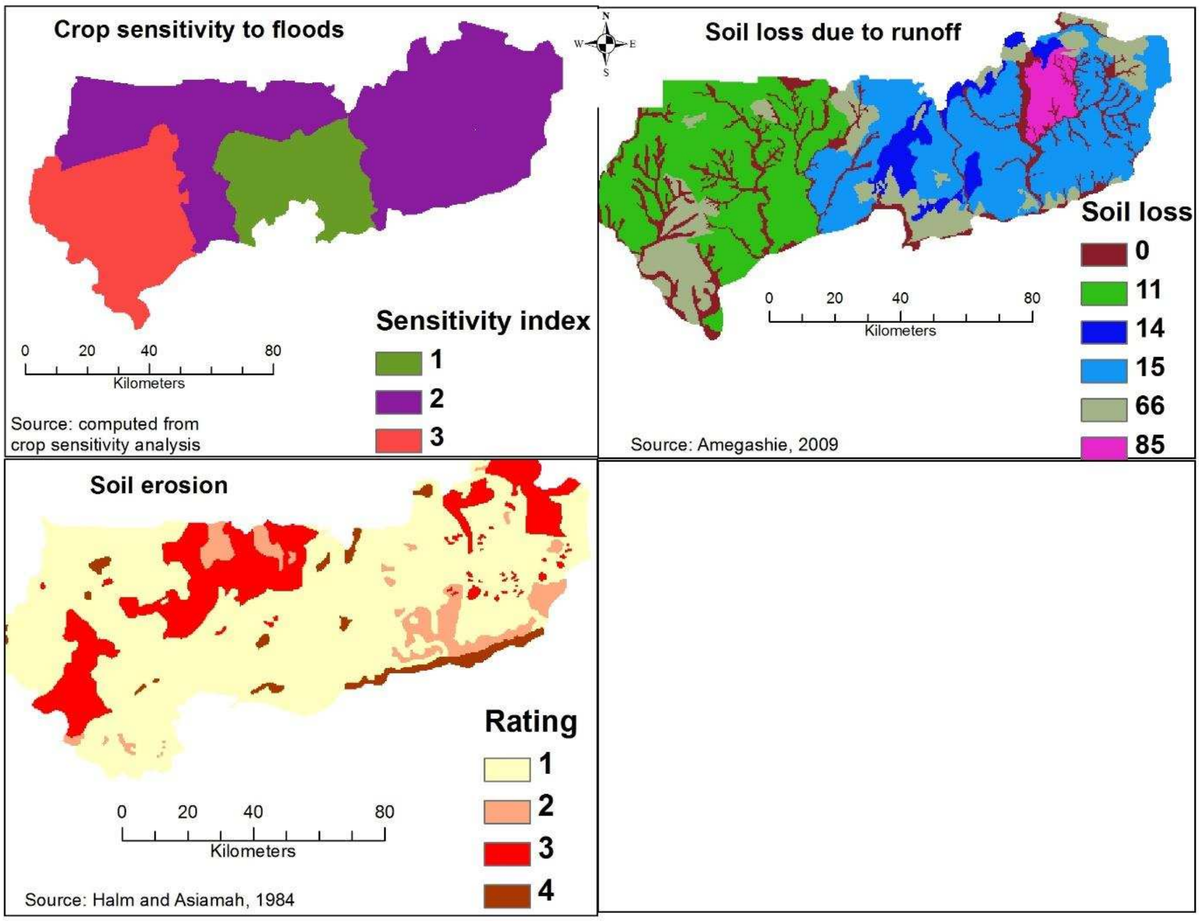

Fig. S6 Susceptibility of agriculture to flooding

The sites where Amegashie sampled were again plotted on the soil map and used to approximate soil and nutrient losses for the types of soils in the area. This was done based on earlier assumptions made when considering the WHC in the section of susceptibility of agriculture to drought/high temperatures. The soil losses determined were assigned to the various types of soils. Amegashie's sampling was done in 2009 at different locations within the catchment of each reservoir using modern equipment and scientific methods of data collection and analysis. Together, these datasets were combined to map the soil loss indicator. The maps are shown in

Fig. S6. For crop sensitivity, the Builsa Districts were more susceptible while the Talensi, Nabdam and Bolgatanga Municipality were less susceptible. As shown in the soil erosion and soil loss maps, the Builsa Districts have a large area with high erosion and high soil losses. There is high runoff in these areas and therefore crops are washed away, resulting in high crop sensitivity to floods/heavy rains. It also means that dams/dugouts constructed in these areas are more likely to be silted faster than their counterparts in areas with less soil losses. Riverine soils (soils of riverbed) were again given a score of zero because the soils are considered unavailable for agriculture use.

2.2.2 Health

Floods/high rainfall affects housing and personal properties, and displaces people. The number of people displaced in each district was obtained from the regional National Disaster Management Organisation (NADMO) office and used to create the displacement indicator. This data was collected after the 2010 flood event that was worsened by the opening of the Bagre dam from Burkina Faso; this event is representative of regional flooding patterns but also accounts for recent water management schemes. Districts with more displaced people were considered more susceptible to floods than those with fewer displaced people. The number of casualties (i.e. injured and dead) was also used to create a casualties indicator. Casualty data was also obtained from NADMO. Districts with higher casualties were considered more susceptible to floods than those with lower numbers. Floods/heavy rainfall also leaves behind pools of water that breed mosquitoes, the vector for transmission of malaria. Thus, the districts' susceptibility to malaria was determined from the health burden due to malaria using the percentage of Out-Patient Department's (OPD) attendance, admissions and fatalities in the health facilities at the district level. Districts with high rates are more susceptible to malaria and therefore, floods/high rainfall conditions supporting transmission are generally more prevalent in the rainy season (Ghana Health Service, 2012). When there is a flood, people in the vulnerable group suffer more because they cannot help themselves. The people in this category comprised the elderly (i.e. 85+), children below 10 years old and people living with a disability. Information on these categories of people was obtained from the census data. Districts with higher numbers of these groups were more susceptible to floods than those with lower numbers. These maps are shown in Fig. S6.

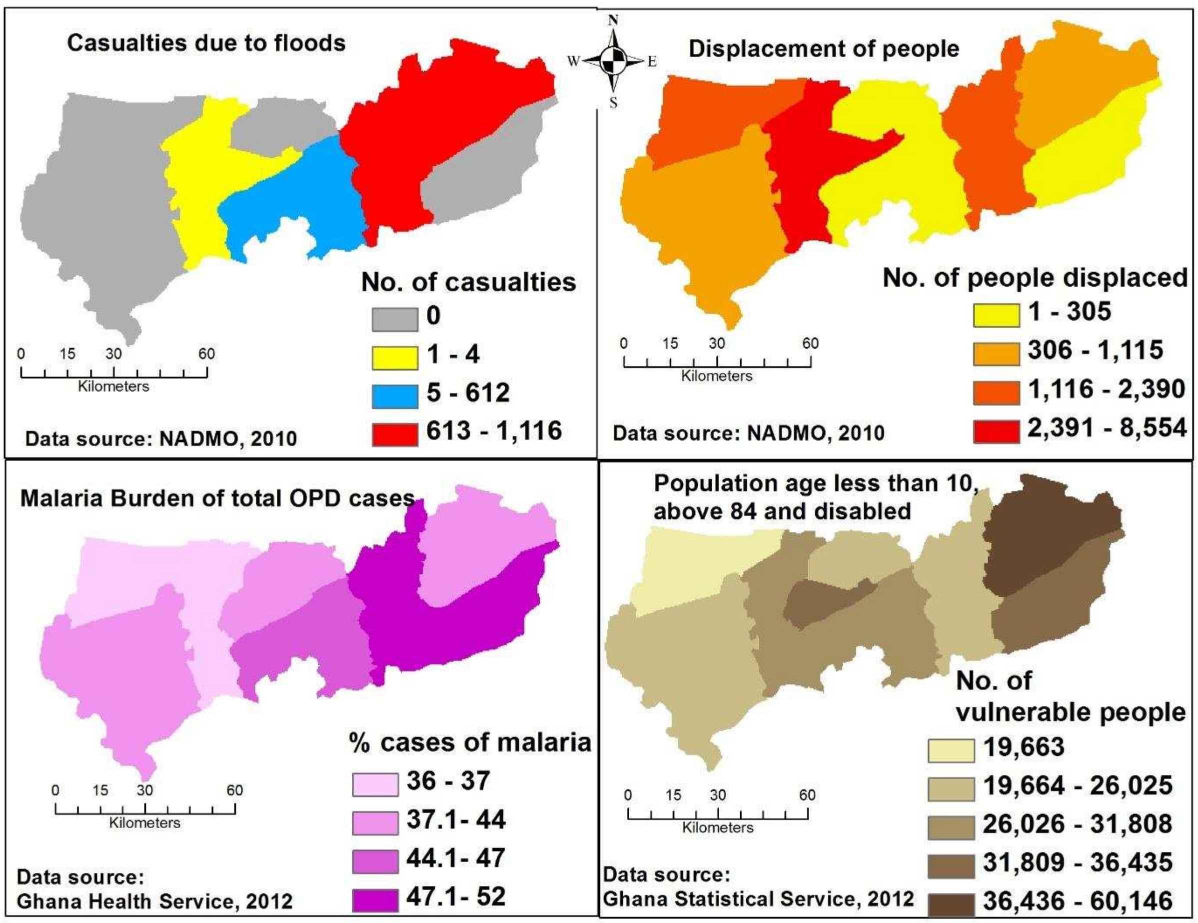

Fig. S6 Susceptibility of humans to floods/high precipitation

2.2.3 Housing

Floods/heavy rainfall affects houses and personal belongings. The number of housing units that were affected in the 2010 floods was obtained from the regional NADMO office. These consisted of houses that were partially or wholly destroyed by floods/heavy rains. Districts with higher numbers of damaged houses were considered more susceptible than those with lower numbers. These data were used to map the susceptibility of the housing units to floods/heavy rainfall. The location of the housing units in terms of proximity to a water body (especially rivers/streams) also exposes them to floods. The closer the buildings are to these water bodies, the more susceptible they are to flooding. Buffers were created from the rivers/streams with distances 500 m, 1000 m and above 1000 m. Those within 500 m were considered very close and assigned a value of 10, 500 to 1000 m were considered near and assigned a value of 5 while beyond 1000 m were considered far and assigned a value of 0. The assignment of these values was based on the categorical scale method (see Nardo et al., 2005). A similar rating scheme was used by EPA (2012).

Flash flooding in the region is more of an urban phenomenon and therefore almost all urban towns were visited to observe the drainage systems in place and their contribution to flooding. The questionnaire survey was also carried out in some of the urban centres which happen to be the district capitals and affirmed the importance of drainage. To rate the places, district NADMO officials were asked about flash flooding history of their urban towns and also 3 additional respondents who stayed in certain localities in the towns were randomly selected and asked informally if they see floods in the vicinity. These findings were combined to deliver the ranks shown in Table S2. The categorical scale was used to assign these scores. Quality of housing also makes the area susceptible to flooding/heavy rainfall.

Table S1 Ranking of localities of flash flooding

Towns/locality	Score
Rural	0
Bolgatanga	5
Bawku/Navrongo/Zebilla/Paga	3
Sandema/Bongo/Garu	1
Tongo/Fumbisi	0

Source (Authors' own construct)

To map this, the percentage of mud buildings in each locality (rural/urban) was determined from the type of building material used in the district. Information was obtained from 2010 census report. This was used as an indicator because mud buildings easily collapse when they become very wet. Maps of the layers to be combined to produce the susceptibility to flooding of the housing sector are shown in Fig. S7.

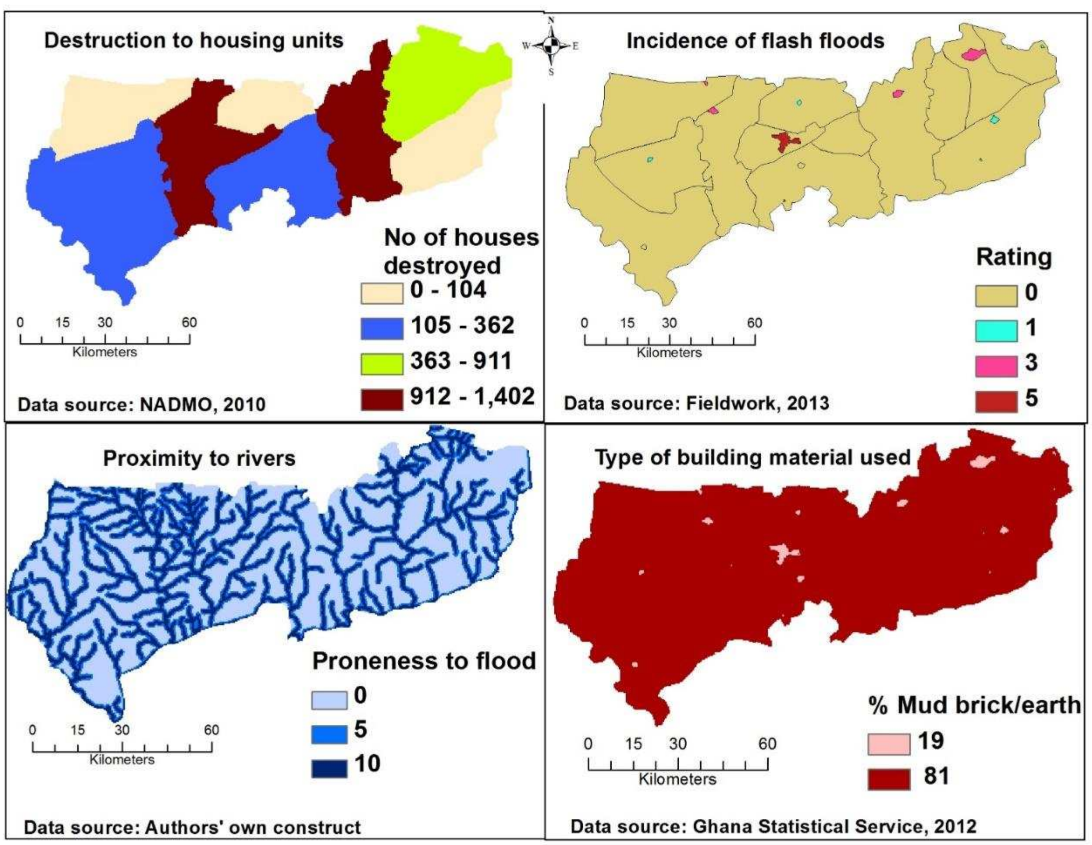

Fig. S7 Susceptibility of the housing sector to floods/high rainfall

2.2.4 Road sector

Floods/heavy rainfall sometimes causes damage to the road network. The damage could entail the road being partially or wholly eroded, or bridges washed away, cutting off communities. When this happens, aid or access to affected communities is also hampered. The susceptibility of the road sector was mapped using the surface of the roads in the area based on the classification by the Ghana Highway Authority (Fig. S8).

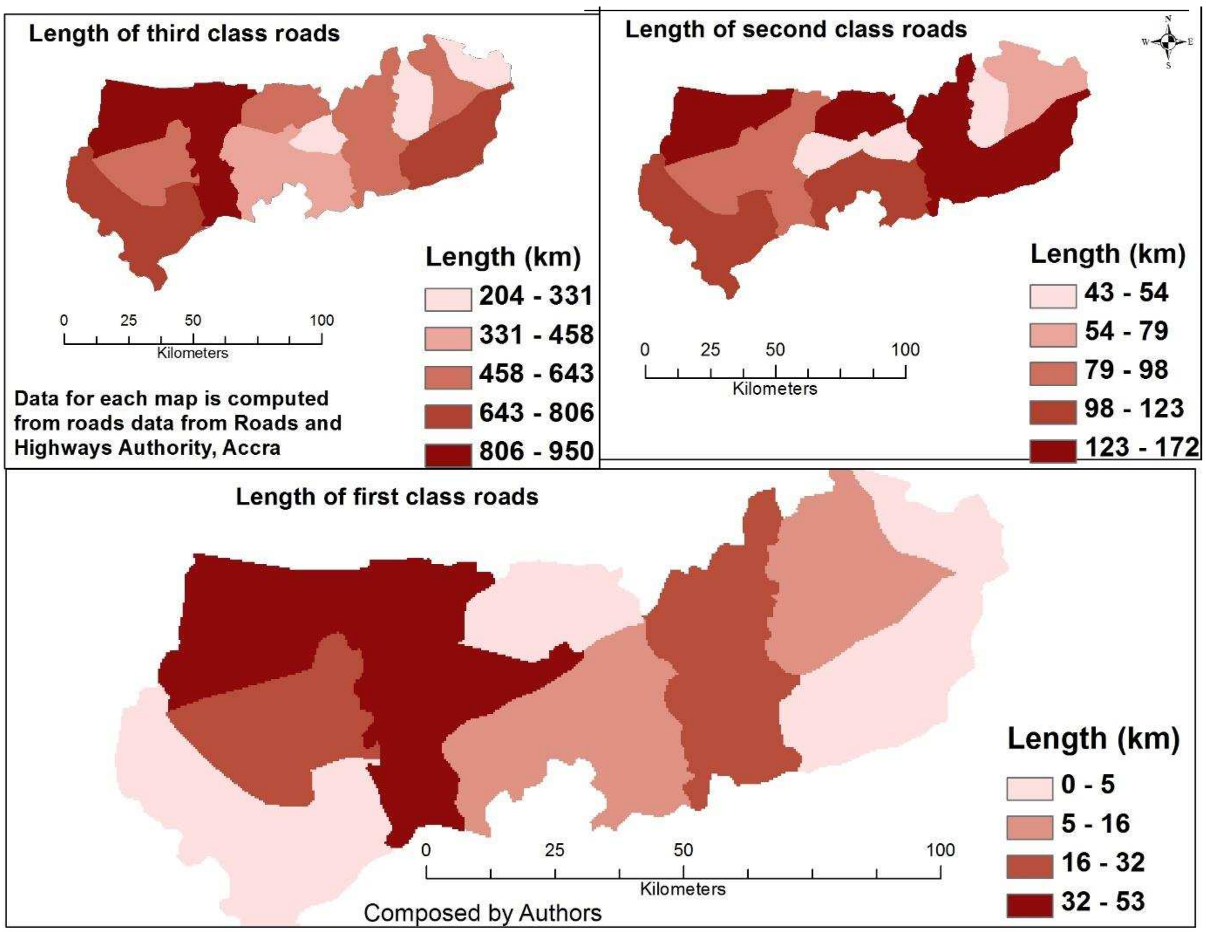

Fig. S8 Susceptibility of the road sector to floods/high precipitation

These classes are defined as follows: first class represents bitumen surface roads and highways, second class represents feeder roads and third class represents tracks and footpaths. The lengths of these roads in the districts were used to map the susceptibility of the roads to floods/heavy rainfall. Tracks and footpaths are more easily destroyed than feeder and tarred roads. The dataset was obtained in GIS shapefile format and classified into these classes. The classification was cross-checked on Google Earth in 2013 to update it with any new roads. Though some of the tarred roads are currently in bad shape and worse than the feeder roads, it is believed that it would not affect the results significantly.

2.3 Susceptibility to windstorms

Windstorms mainly affected roofs of buildings. Although they sometimes pulled some of the crops down, the crops are often able to rise again naturally or the farmers prop them up by supporting the base with soil. It was also gathered from the field survey that the effect of winds is greater on thatch than roofing sheets and that windstorms had no effect on mud roofs. Thus, the percentage of thatch was used to map the susceptibility to windstorms. The percentage of buildings roofed with thatch was obtained from the 2010 census report. Districts with higher percentages of thatch were more susceptible to windstorms than those with lower values. The questionnaire participants attributed the strength of windstorms to the reduction in tree cover which hitherto served as wind breaks. The savannah woodland cover from the classification of the 2010 Aster image was used as a proxy. The argument is that places with high tree density will have high tree cover to serve as wind breaks and therefore will be shielded from the effects of windstorms. Based on discussions with community members and observation of disparate measures in the villages as well as literature, the ratings in Table S3 were assigned to each land cover using the categorical scale. Places with lower tree density were considered more susceptible to windstorms and were assigned higher scores. The maps for the windstorms are shown in Fig. S9.

Table S2 Rating of land cover types for windstorm susceptibility based on tree density

LANDCOVER	weight
Grass/herb with/without scattered trees (0-5 trees/ha)	50
Widely open cultivated savannah woodland (6-10 trees/ha)	40
Open cultivated savannah woodland (11-20 trees/ha)	30
Open forest (<60 %)	10
Closed savannah woodland (>25 trees/ha)	20
Reservoir	50
Riverine savannah vegetation	10

Source (Authors' own construct)

The metal sheets are attached more securely than thatch roofs, which are fastened with jute. It is also realised that the areas to the eastern part, central and some parts in west of the region have less tree cover and are more susceptible.

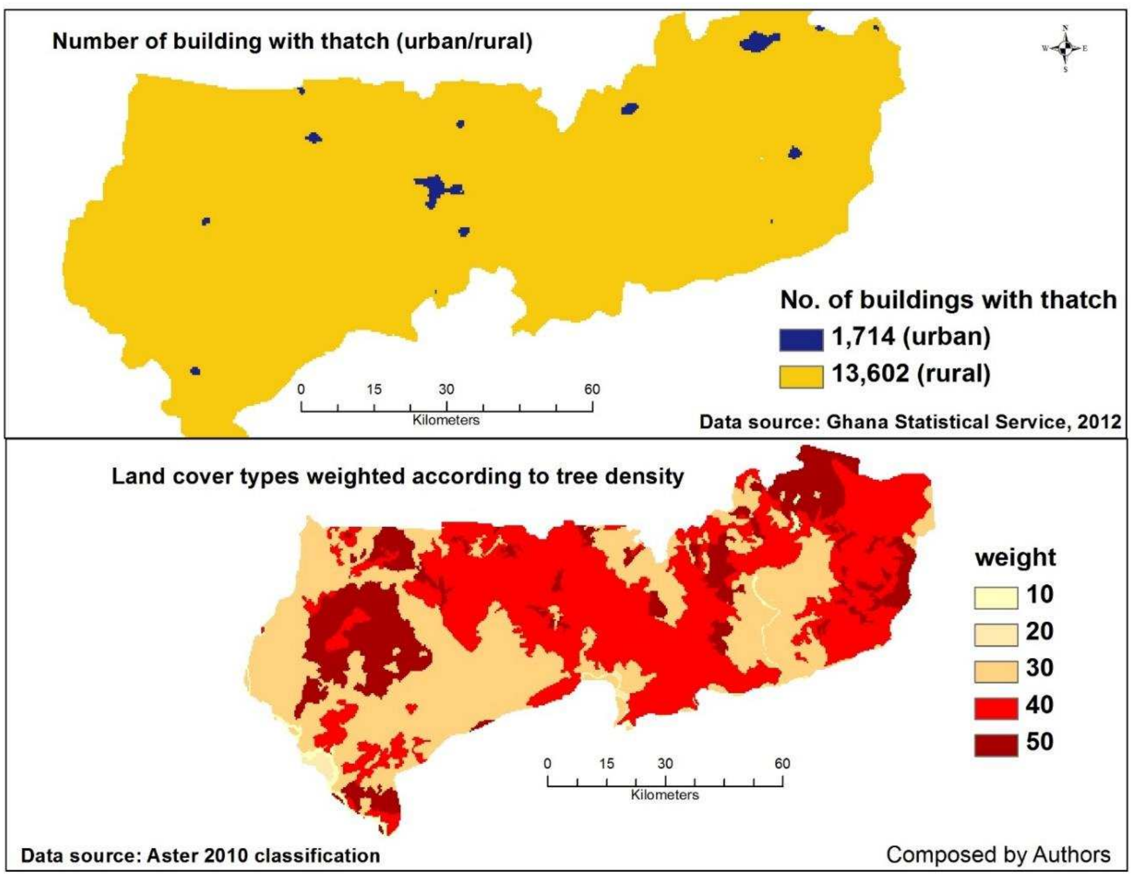

Fig. S9 Susceptibility to windstorms

In this area, largely north of the Intertropical Convergence Zone, winds are from the East/Northeast, and are stronger as they sweep across vast areas of unprotected land.

3 Adaptive capacity indicator datasets

Adaptive capacity encompassed both socio-economic and natural/technological factors that the people use to respond to the hazards. The indicators identified as adaptive capacity are summarised in Table S4. These indicators in Table S4 are grouped into the five livelihood capitals and discussed in the next subsections.

Table S4 Adaptive capacity indicators

Agriculture Sector		**Health Sector**	
Resilience	**Social**	**Resilience**	**Social**
Remittances	Wealth	Electricity	Wealth
Markets	Financial institutions	Health facilities	Literacy
Animal ownership	Investment opportunities	Income generating activity	
Irrigation facilities	NGOs	Markets	Early warning
Protected land	Institutions	Food aid	Skill
Land availability	Skills	Remittances	
Income generating activity	Literacy	Land availability	
Water		Animal ownership	
Electricity	Institutions	**Housing**	
Income generating activity	Investment opportunities	Remittances	Institutions
Land availability	Skills	Land availability	Wealth
	NGOs	Income generating activity	Literacy
	Wealth		NGOs
Road			Skills
Land availability	Institutions		
	NGOs		

Source: Authors

3.1 Human capital component

The human capital indicator was mapped using the level of skills and education of the people in the region. The literacy rate for each district was used to create a layer for education. The rationale is that the more literate population a district has, the better its chances of having more people in other (non-agriculture based) forms of employment, and hence a higher adaptive capacity. This data was obtained from the census 2010 report. The levels of skills of the district were assessed using the number of people employed in industries that are skill based. This was calculated from the 2010 census report indicating the number of economically active people in employment by region and locality. Occupations that did not require skills or training and agriculture were excluded.

3.2 Social capital

In each district, there are a number of NGOs lending support to the people. NGOs undertake a range of activities from advocacy to capacity building. Some of the NGOs provide these activities to organised groups and therefore encourage people to associate. These activities strengthen capacities to cope with the environment. The number of NGOs was obtained for each district from the institutional questionnaire, and supplemented with the list from the district profiles, and used as an indicator to map social capital. Thus, the higher the number of NGOs operating in a district, the better its social capital.

There are decentralised government institutions in the region in charge of managing some of these hazards, either directly or indirectly. The institutional capacities of institutions in the region were assessed. These institutions rated themselves in terms of the financial, physical, technological and human capacities to deal with the hazards as part of their responses to the institutional questionnaire. Interviews with institutional heads or representatives sought to find out their rate of response when a hazard occurs. The response level of the institutions was assessed by the community members. This assessment resulted in scores of 10 and 3 for institutional capacity for urban and rural districts respectively, using the categorical scale. These were used to identify the institutional capacity. The maps resulting from the data described above are shown in Fig. S10.

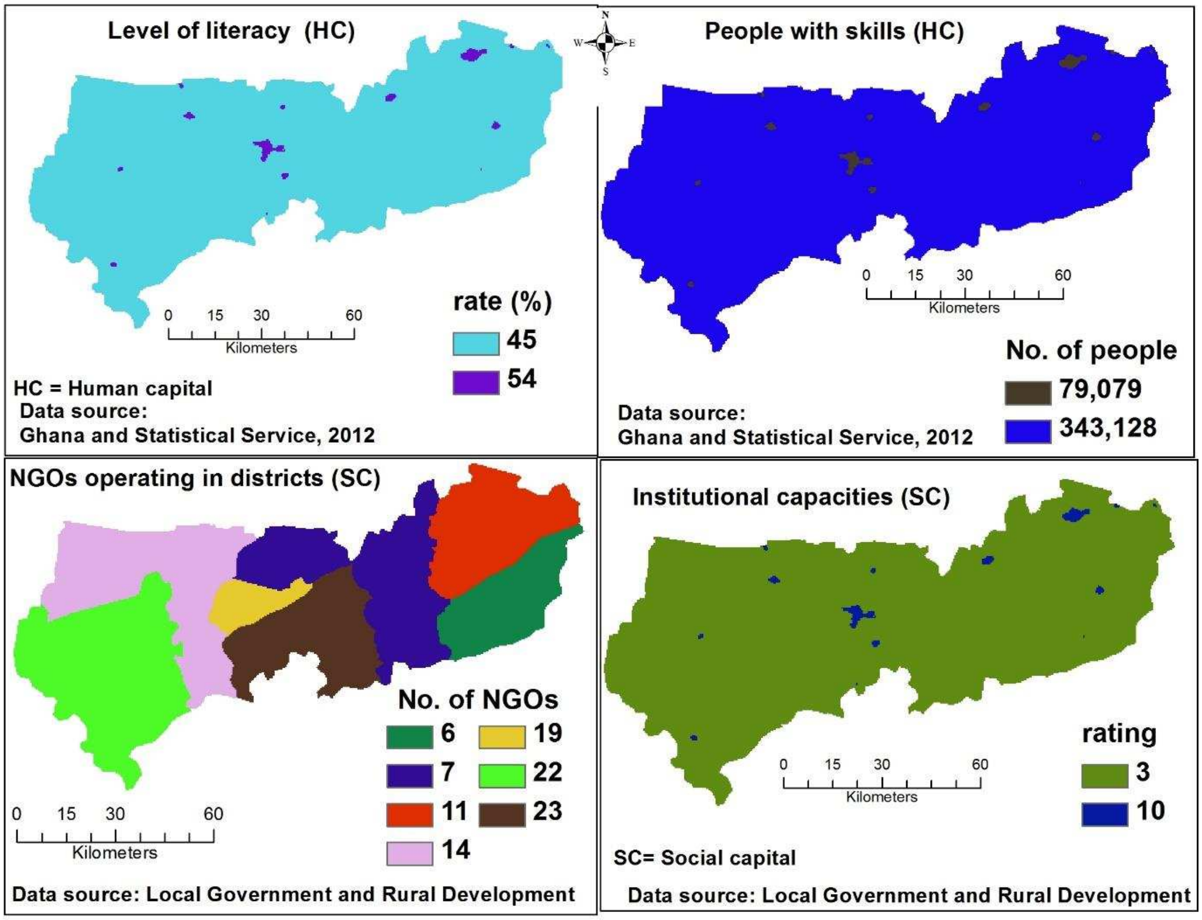

Fig. S10 Maps of Human and Social capitals

3.3 Financial capital

Financial wealth, presence of financial institutions, and investment opportunities as well as employment status, were used to map this component. Although a complex indicator, in general, financial wealth is a very good indicator of adaptive capacity as it shows the ability of people to command resources to respond to hazards. The data for this was obtained from the WFP (2012) report and supplemented with the data from the census report to segregate into urban and rural households.

Financial institutions play a role in providing credit to support the victims of hazards. The financial institutions are the mainstream banks and micro-credit agencies or NGOs which source funds and give them to the community members in the form of credits for their livelihood activities. The number of financial institutions in a district was obtained from the district assembly's profile and used to map this indicator. Though some of these financial institutions operate within the urban areas, a few of the rural people who are able to meet the requirements of the banks get access to credit. The type of financial institution was considered in determining the rating for the district. For example, a national or commercial bank is put in a higher level than a rural bank, an NGO and a micro credit facility. Table S5 shows the ratings given. A district with a higher score was considered more financially sound than those with lower scores.

Table S5 Scores of financial institutions in the districts

	Type of institution								
	National bank		**Rural bank**		**NGO[2]**		**Microcredit**		**Total**
District	**No.**	**Rating**	**No.**	**Rating**	**No.**	**Rating**	**No.**	**Rating**	
Bawku Mun.	2	10	1	5	3	2	1	1	32
Bawku West	1	10	1	5	1	2	2	1	19
Binduri	0	10	1	5	3	2	1	1	12
Bolgatanga	7	10	3	5	3	2	2	1	93
Bongo	0	10	1	5	1	2	1	1	8
Builsa North	0	10	1	5	1	2	1	1	8
Builsa South	0	10	0	5	1	2	1	1	3
Garu-Temapne	0	10	1	5	3	2	1	1	12
KN East	1	10	1	5	2	2	1	1	20
KN West	0	10	1	5	2	2	1	1	10
Nabdam	0	10	0	5	4	2	2	1	10
Pusiga	0	10	1	5	3	2	1	1	12
Talensi	0	10	0	5	4	2	2	1	10

Source (Authors' own contruct)   KN= Kassena-Nankana

[2] NGOs are those specifically providing financial assistance. The rating was arbitrary but based on financial capacity on the institutions

It must be mentioned here that although some of the NGOs may be richer and do more than the rural banks, they are rated lower than the rural banks because banking is not their core business. The investment opportunities in the districts also boost their capacity. In the district profile, the number of investment opportunities in operation was used to map this indicator. Thus, a district with the higher number of investment opportunities is adjudged to have better opportunities and hence a higher adaptive capacity. Maps are shown in Fig. S11.

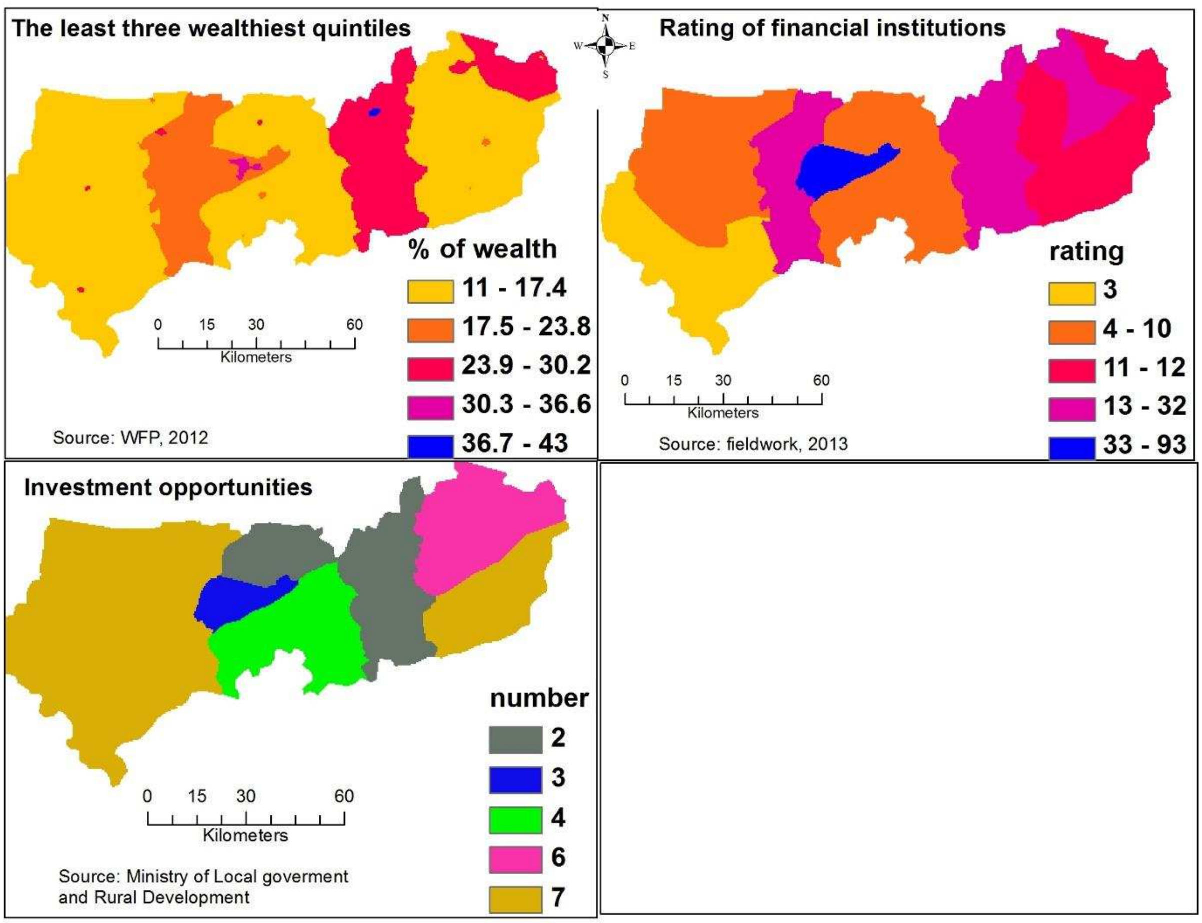

Fig. S11 Financial Capital

3.4 Natural assets

The availability of the natural environment as well as its integrity is key for adapting to hazards. This is because the people depend on natural resources to eke a living. The natural assets component was mapped using indicators such as availability of land for human activities and protected areas. It does not consider accessibility or property rights though. The size of each district was calculated and used to map the indicator for land availability. The rationale is that the size of land available in a district determines capacity to use that land to engage in a range of activities, and that this will enhance its capacity to deal with hazards. Other natural assets such minerals are part of the investment opportunities under financial capital and are therefore not considered here. The dataset was obtained from the GIS database. Another ecosystem integrity indicator that was mapped was the presence of protected forest per district. The areas of reserves per district were calculated and used.

3.5 Technology

This subsection covered the availability of technology and its use to better the livelihood activities of the people. Thus, it covered topics like the use of irrigation systems and early warning systems. An early warning system is in place. To map the capacity of the districts in terms of early warning systems, the effectiveness of the system was measured from the questionnaire survey responses on how people use the information received from the early warning system. Districts with low percentages represented those where a large number receive the information but do nothing with it because either it does not matter to them or they got the information too late and therefore could do very little with it. The analysis also showed that the early warning information was always sent out when there is evidence for floods or windstorms but never for droughts. This was apparent from the usefulness of the information: respondents moved their properties, harvested their crops, or secured their roofs before these floods or windstorms occurred. The information for this indicator was generated from the questionnaire survey and institutional survey.

Irrigation dams/dugouts are used for dry season farming. To map this indicator as a capacity to adapt, the catchment area of the dams/dugouts was determined from the data obtained from IDA (2013). The reasoning is that dams/dugouts with large catchment areas have the capacity to store more water for dry season farming than those with smaller catchments. The catchments of the two big dams in the region (Tono and Vea) extend into Burkina Faso and some of their tributaries are dammed, but the catchment area within Ghana only was used. Maps for the natural capital and technology are shown in Fig. S12. Land availability is high in Bawku West and Builsa South Districts and low in Bolgatanga municipal and Nabdam District.

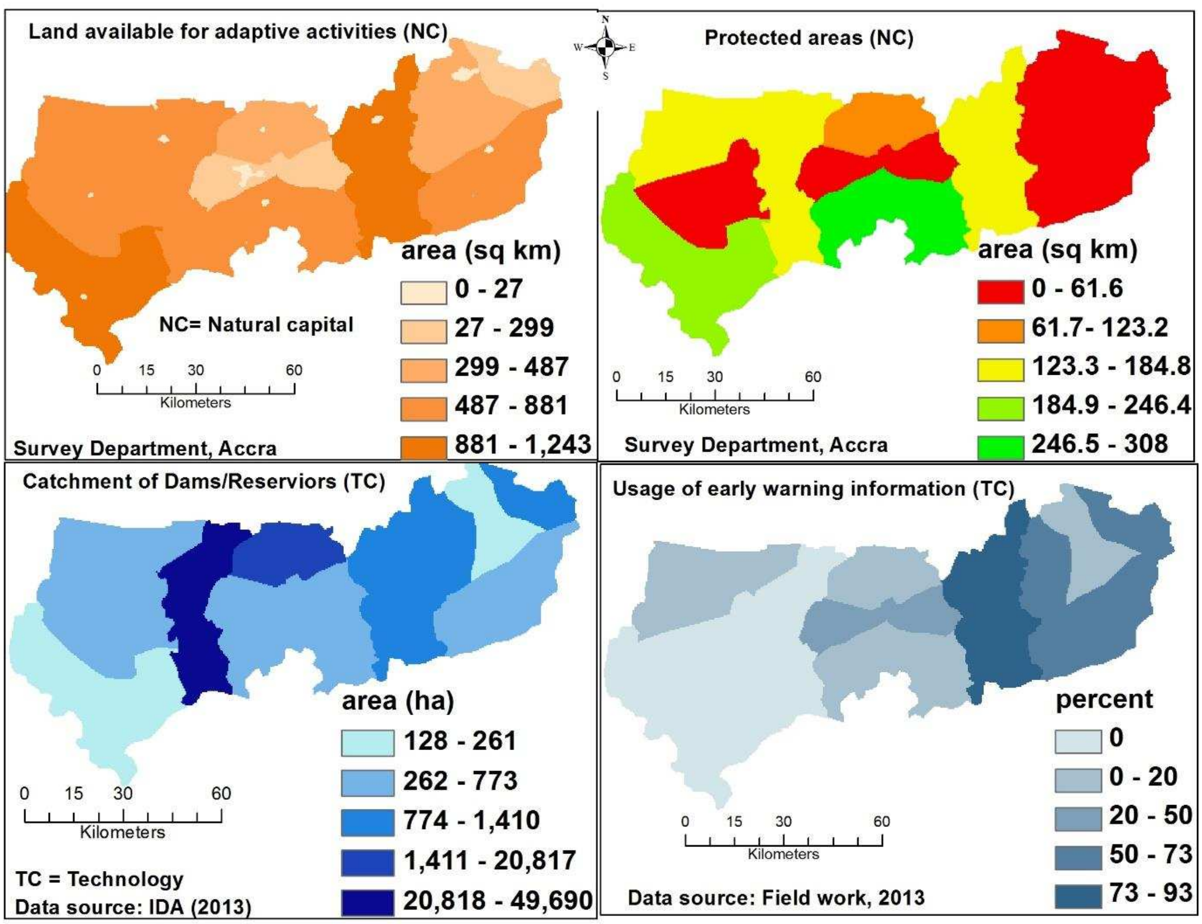

Fig. S12 Maps of Natural capital and Technology

It is also low in the urban areas due to urbanisation. Builsa South and Talensi Districts have high numbers of protected areas while Bawku municipal has the lowest. Kassena-Nankana East has more area under irrigation. This is expected because the largest irrigation scheme is located in this district and it has the highest number of reservoirs. It is also seen that use of information from the early warning system is high in the eastern part of the region.

3.6 Infrastructure

The indicators under this subsection relate to accessibility to services such as health, education, transport and the presence of markets. Health facilities were rated in the districts based on level of service, staffing logistics and facilities. For simplicity, all hospitals in the region were put in the same category. The problem with the simplification is that some hospitals are better than others in terms of service, structures, staffing, and infrastructure, but collecting these details was beyond the resources of this project. This approach has generally been used by the Regional or Districts Health Directorates when reporting the number of hospitals or classifying health facilities. Similarly, maternity homes were put in the same category as a Community-based Health Planning and Services (CHPS) compounds. Maternity homes only offer care to maternal mothers. The ratings are shown in Table S6. It is assumed that districts with higher ratings have better infrastructure and a higher adaptive capacity, health wise. Access to health services is critical because it represents the districts' capacities to handle diseases and ailments and injuries relating to the hazards. The markets however, were rated based on the level of service, functions and structures. For educational infrastructure, the number of schools in each district was used. This was because with the exception of basic schools which need to be closer to the pupils, the others are accessible to everybody. Therefore no ranking was done regarding educational infrastructure. Electricity was also used to map the adaptive capacity in relation to these hazards.

Table S6 Ratings of Markets based on functionality and structures

District	Hospital		Health Centre		Clinic		CHPS		Maternity Home		Total	Market[3]	Rate
	N	R	N	R	N	R	N	R	N	R			
Bawku Municipal	2	200	6	50	9	30	16	5	1	5	1055	Bawku	50
Bawku West	1	200	4	50	10	30	14	5	0	5	770	Zebilla	30
Bolga Municipal	2	200	7	50	7	30	14	5	0	5	1030	Bolga	50
Bongo	1	200	5	50	1	30	27	5	0	5	665	Bongo	20
Builsa	1	200	6	50	0	30	21	5	0	5	605	Sadema	30
Garu Tempane	0	200	6	50	6	30	26	5	0	5	610	Garu	30
Kassena-Nankana E	1	200	2	50	3	30	18	5	0	5	480	Navrongo	50
Kassena-Nankana W	0	200	6	50	1	30	25	5	0	5	455	Chiana	30
Talensi Nabdam	0	200	3	50	5	30	16	5	0	5	380	Tongo	20

Source (Authors' own construct) N.B: N=number, R=rate assigned.

Electricity is needed to power the cooling systems in the face of rising temperatures and to ensure some of the systems run efficiently. The electricity usage was measured by the level of coverage. It must be noted that close to 96% of electricity is consumed by urban dwellers with about 4% consumed by rural dwellers (Ghana Statistical Service, 2012). See Fig. S13 for maps.

[3] The new districts also had markets were rated as Ambrose (Binduri)=30, Fumbisi (Builsa South)=20, Pusiga = 30 and Pelungu (Nabdam)=30

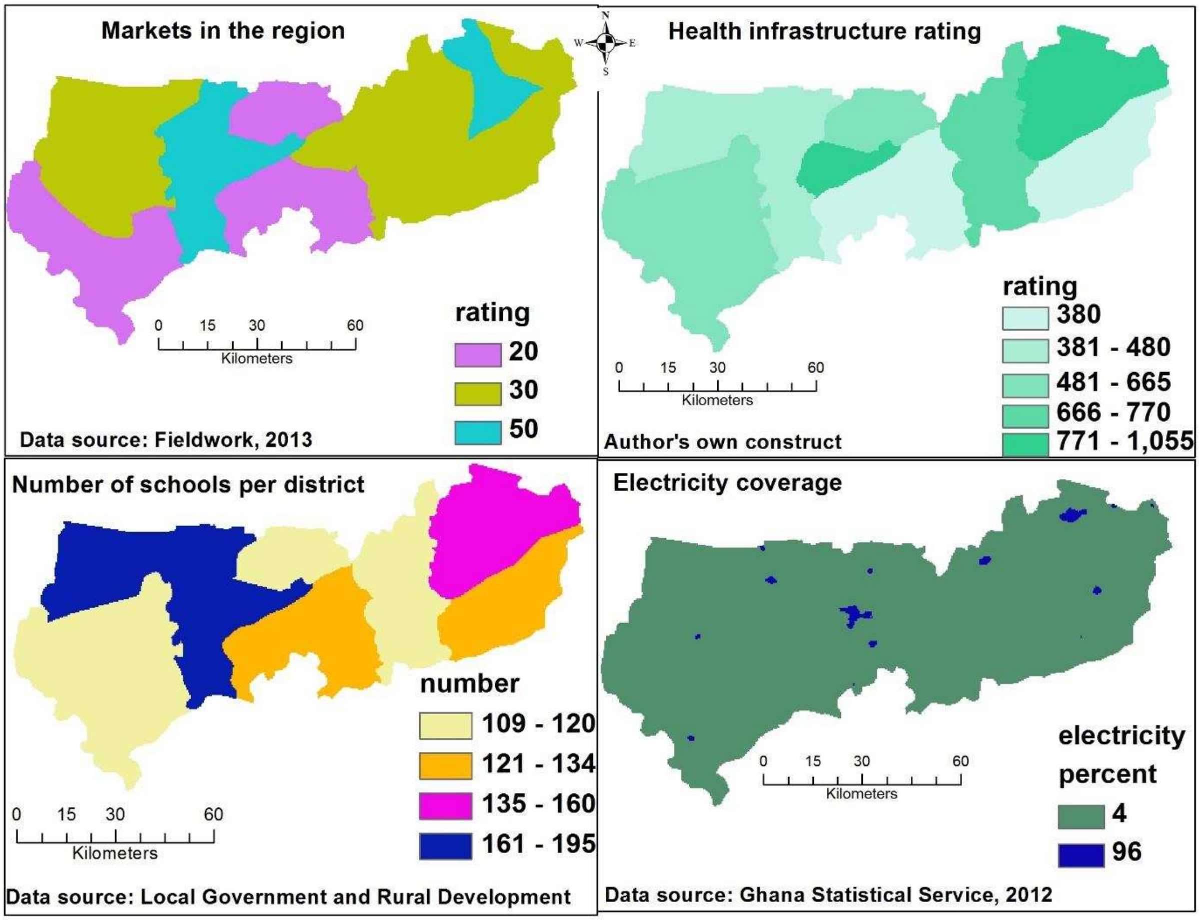

Fig. S13 Maps of infrastructural coverage

3.7 Coping strategies

Remittances received from relatives living outside of the districts were used as a measure of coping. This was considered a coping strategy because remittances were largely used for buying food, agricultural inputs or to rebuild/rehabilitate housing units. Thus, from the questionnaire survey, the percentage of households receiving remittances specifically for coping with disaster was extracted, combined with remittances from the WFP (2012) report and used to map this indicator. Most remittances go into buying food and help the people cope with food shortfalls from their own production and consequently crop failure. Another coping strategy was rearing livestock and selling them off in times of need. The dataset to map livestock ownership was derived from the WFP (2012) report which presents district level data. From the dataset, households with large livestock ownership had more coping capacity as they can sell more than those with lower numbers. Livestock ownership did not include poultry because incomes from poultry are generally low.

Also, the people are engaged in income generating activities such as food processing, petty trading, and corn mill operations, which yield additional income to support the household. The average number of household members engaged in income generating activities was used to map this indicator. Districts or areas with high percentages are assumed to be more resilient than those with low values. This dataset was obtained from the WFP report (2012). Another indicator identified was food aid. The dataset to map this indicator was obtained from the WFP report. It showed the percentage of households receiving food aid in each district. Households receiving food aid increased their ability to cope with food shortages resulting from low production on their farms. Thus, districts with a higher percentage of households receiving food aid had a higher coping capacity than those with lower percentages. The maps for coping capacity are shown in Fig. S14.

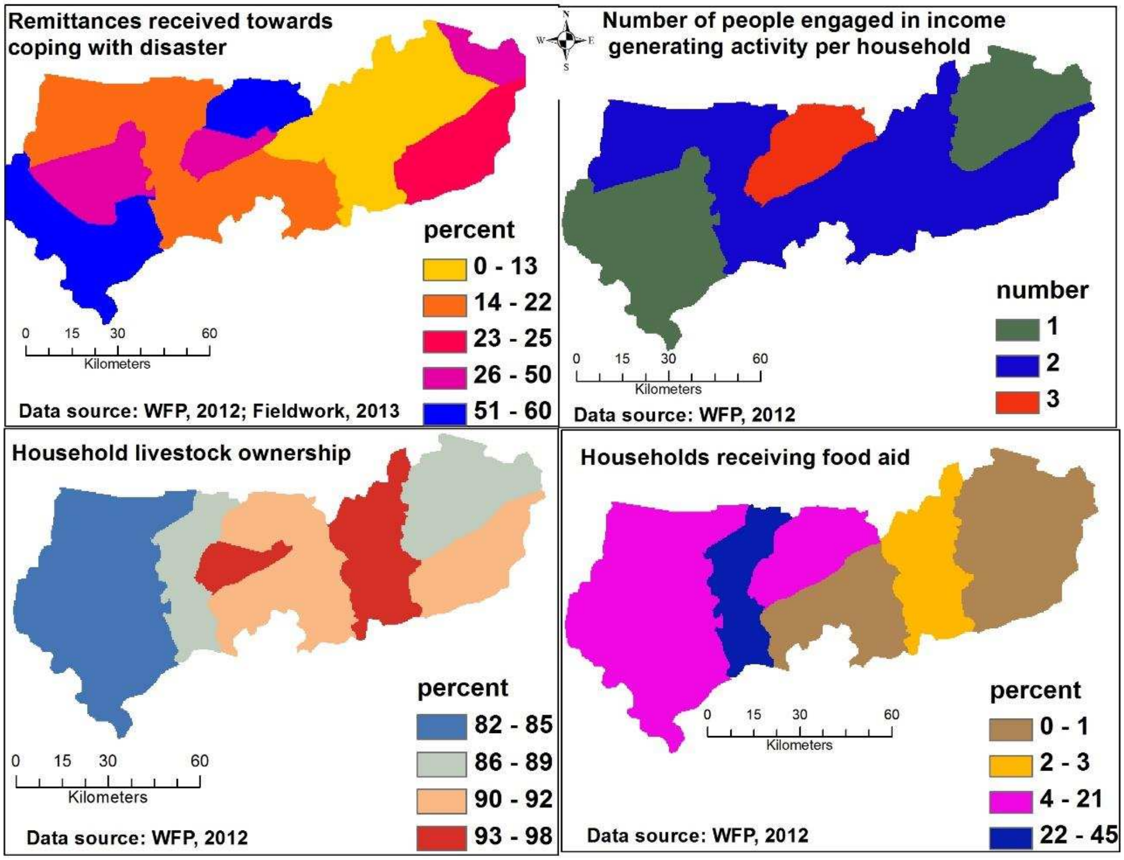

Fig. S14 Coping capacity of households in the districts

4. Normalisation

As can be seen in Figures S2 – S14, indicators used different units of measurement. Thus, indicator data were normalised and brought to a uniform dimension to avoid problems with mixed units. The rescale method (eq. 1) was used (see Malczewski, 2000; Nardo et al., 2005).

$$\text{Normalised value} = \frac{\text{value to be normalised} - \text{minimum}}{\text{maximum} - \text{minimum}} \qquad \text{eq. 1}$$

The normalised value represents the results obtained after substituting the values in a dataset into the equation. Eq. 1 rescales all values in a dataset to range between 0 and 1. This method has been used in several studies (e.g. Damm, 2010; Abson et al., 2012; Yiran, 2016). The rescale method avoids the use of positive and negative values of an indicator in the aggregation process, which makes interpretation of the composite indicators more complex.

5. Evaluation

Evaluating a composite index is one of the most important steps in a quantitative vulnerability assessment as both the development of indicators and the building of a composite index inherits numerous uncertainties (Damm, 2010). All steps taken during the development of indicators, from gathering of data and information from various sources, scaling of data, and finally the selection of a normalisation, weighting and aggregation technique, involve subjective decisions that severely contribute to the existence of uncertainties (Nardo et al., 2005). Thus, indicator development and building a composite index inherit numerous uncertainties (Damm, 2010). Nardo et al. (2005) emphasise the importance of evaluating uncertainties. Therefore, we tested the normalisation, weighting and aggregation procedures and composite indices for uncertainties (robustness and sensitivity).

Normalisation was tested by using the standardised score which normalises indicators to have a mean of 0 and standard deviation of 1 (eq. 4):

$$\text{Standard score} = \frac{Value - mean}{standard\ deviation} \quad \text{eq. 4}$$

Weighting was tested by assigning equal weights to all indicators, because equal weights require no subjective interpretation, and disguises the absence of statistical or empirical facts (Nardo et al., 2005). Finally, geometric aggregation (eq. 5) tested the robustness of the selected additive aggregation technique.

$$CI = \prod_{q=1}^{Q} X_q^w \quad \text{eq. 5} \quad \text{(Nardo et al., 2005)}$$

CI = Composite Indicator, q = sub-indicator, w = weight associated to sub-indicator

Sensitivity analysis computed the mean volatility between the various composite indicators and the procedures mentioned above. Volatility is determined by the standard deviations of the ranks of indicators (Groh et al. 2007).

Although all indicators were tested, the agriculture sector is presented here for illustrative purposes. The results of the robustness tests are shown in Fig. S15.

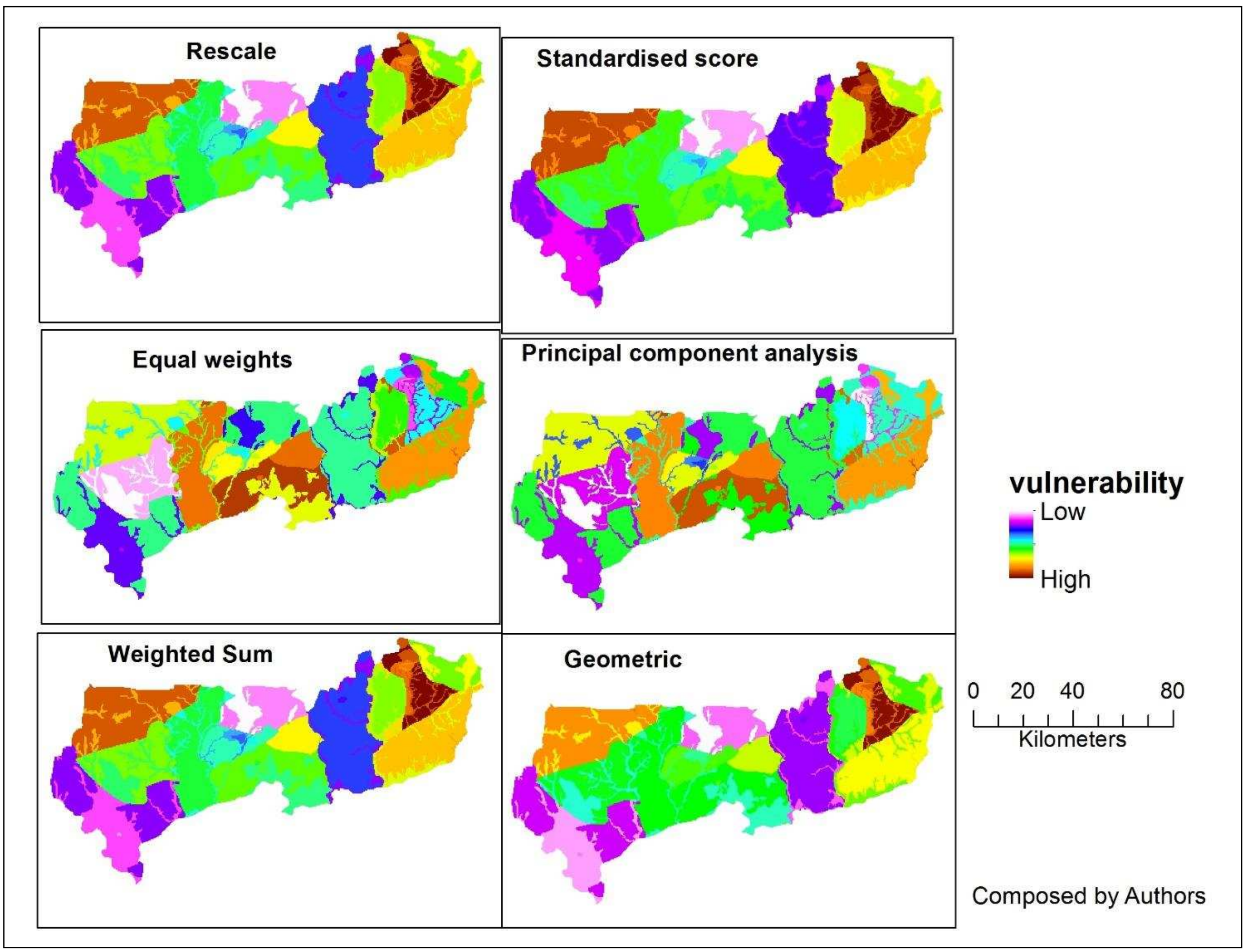

Fig. S15 Test for Robustness with the normalisation and weights

As can be seen in Fig. 15, the same high vulnerability areas are indicated in each pair. It can also be observed that the vulnerabilities exhibit the same patterns although there are variations across the region.

Mean volatilities of different scenarios were computed by excluding indicators in turn to test sensitivity to each of the indicators. For the agriculture sector, composite vulnerability was calculated an additional 7 times, excluding, crop sensitivity, grassland (pasture), Water Holding Capacity (WHC), investment opportunities, institutional capacities, land availability and protected land each run (Table S7). Table S7 shows volatilities range from 0.17 to 0.21. The vulnerability indices therefore changed very little and were not sensitive to any indicator. Thus, the indices were relied on to assess the nature of vulnerability. In doing this, we constantly make reference to the original indicators.

Table S7 Mean volatility of nine scenarios

Variable excluded	WHC	Pasture	Crop sensitivity	Institutional capacity	Investment opportunity	Land availability	Protected land
Volatility	0.2	0.2	0.21	0.19	0.18	0.19	0.17

Source (Authors' own construct)

The vulnerability to windstorm is shown in Fig. S16. Refer to main paper for description.

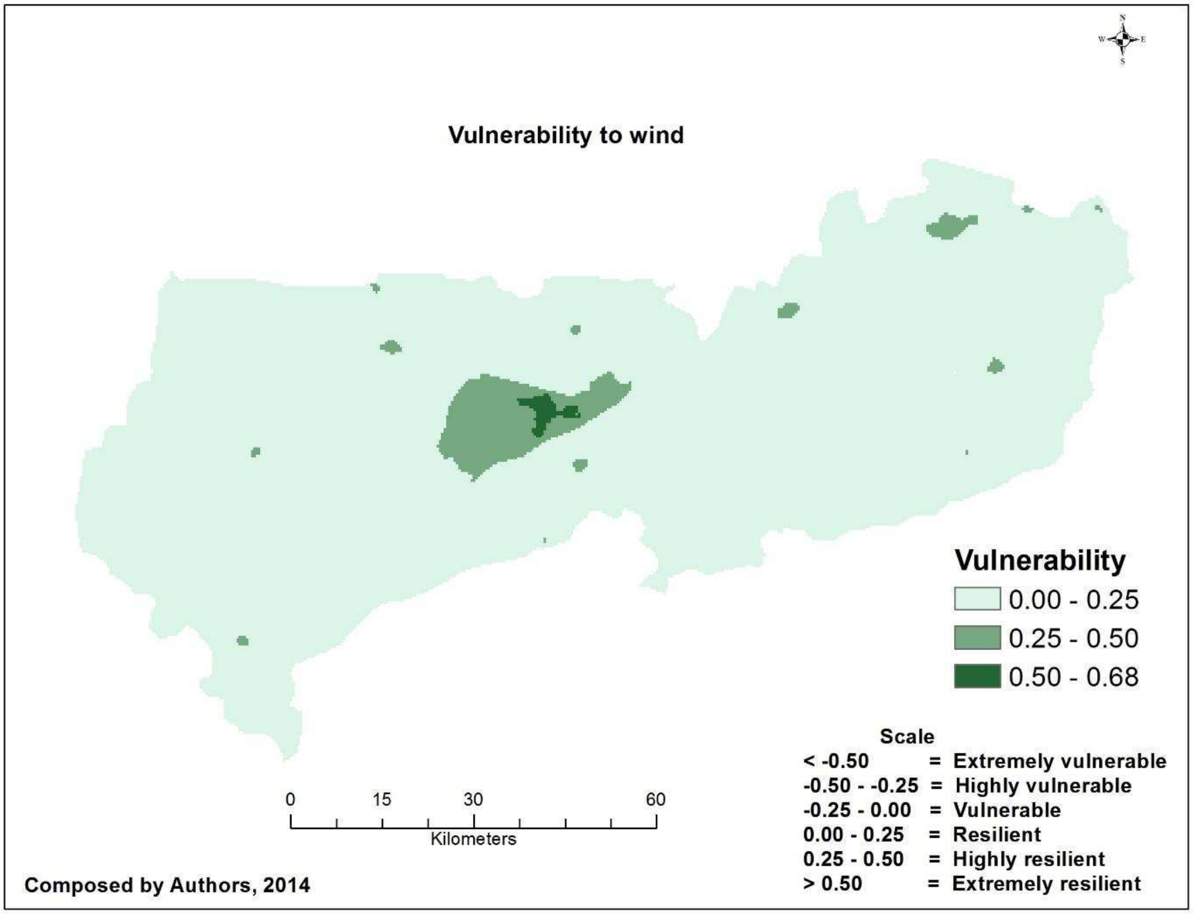

Fig. S17 Vulnerability of the UER to windstorms

5.0 Conclusion

This supplementary material presented information on the indicators used for the vulnerability mapping of the various hazards occurring in the savannah ecosystem. It outlined how data on the indicators were collected and converted into geographic layers for the mapping exercise. The maps show that the susceptibilities and adaptive capacities of the sectors vary among the districts for the various hazards and this may produce variation in vulnerabilities.

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