

# Spatially Explicit Modelling of Extreme Weather and Climate Events Hot Spots for Cumulative Climate Change in Uganda

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## Abstract

*The reality of climate change continues to influence the intensity and frequency of extreme weather events such as heat waves, droughts, floods, and landslides. The impacts of the cumulative interplay of these extreme weather and climate events variation continue to perturb governments causing a scramble into formation of mitigation policies. However, national scale composites of climate hotspots remain a bottle neck to this policy formation. This paper therefore, modelled the spatially explicit extreme weather and climate events indicators into a Uganda-national extreme weather and climate events composite hotspot indicator model. The hotspot model was mapped into decomposable sub-indicators based on the Geon concept. A spatial indicator framework was developed through literature review and expert knowledge. The resulting indicators were weighted using Principal Component Analysis (PCA) /factor analysis and then normalized. They were aggregated using Multi Criteria Decision Analysis (MCDA) tools in an Object Based Image Analysis (OBIA) environment. Sensitivity analysis was carried out to ascertain the influence and significance of the indicators in the resultant model. A cumulative climate change index model was hence analysed and mapped. The mapping provides spatially explicit information regarding climate extremes at national scale, consequently addressing its growing demand among public and private institutions. Further research, into the complex interactions of cumulative climatic factors and external components like ecological systems and anthropogenic biomes will go a long way in boosting climate information. This coupled with easy access to open web availability; if adopted, will readily inform national climate change policy at national level and greatly improve decision making within development sectors, hence mitigating the advance effects of climate change.*

## 1. Background

Climate change is a global reality, and Uganda is no exception. Although developed nations contribute higher levels of greenhouse gases (GHG), developing nations like Uganda that have had miniscule contribution to global warming are feeling the impacts of climate change first and worst (Oxfam, 2008). According to Hepworth (2010), if the GHG emissions are not reduced, climate models consistently show an increase in global temperatures of up to +4.30C, and +3.20C in East Africa by 2080. Similar consistence is observed in the models projecting a 7% increase in wetter conditions in the same period. These variations are likely to mean; increased food insecurity, soil

erosion and land degradation, flood damage to infrastructure and settlements, shift in spread of diseases like malaria and shifts in agricultural productivity and natural resources. Such consequences of climate change inherently make Uganda highly vulnerable to the impacts of climate change (ACCRA, 2010).

Lavell et al., (2012) propose that, extreme weather and climate comprise the main facet of climate variability under stable or changing climate. They further define extreme events to mean the occurrence of value of a weather or climate variable above or below a threshold value of the range of observed values of the variable. Similarly, the IPCC, (2012) summary to policy makers argues that managing the risks of extreme events and disasters to advance climate change adaptation is best approached by assessing the scientific literature on issues that range from the relationship between climate change, extreme weather and climate events to their implications for society and sustainable development. Therefore, as much as the character and severity of impacts from climate extremes depend not only on extremes but also on exposure and vulnerability, this study explored and focused on the weather and extreme climate events that provide assessment concerns to a policy maker as a result of the interaction of climatic extremes with environmental and human factors triggering impacts and disasters.

Of recent, Climate change has forced itself on the agenda among Ugandan government ministries and agencies and is perceived as a 'hot topic' consequent to weather extremities of the 2007 floods, landslides, high temperature spells and repeated drought (Hepworth and Goulden 2008). Inevitably, government bodies and forums have scrambled into developing climate change related adaptation and mitigation policies. This is intended to shift the disaster management paradigm from the traditional emergency response focus to one of prevention and preparedness (Kaggwa et al., 2009). The climate assessments that associate national policy development deal with several spatial climate related indicators. However, these are often availed at global scale rather than national scale; and at single indicator and not composite indicator interaction level. The rarely resultant hotspot composites are also not often decomposable to sub-indicators and open accessibility to them remains a challenge. This creates a problem of non-precise national climatic composite assessments. Availing a framework for a regionalized decomposable and national climate hotspot index, will thus go a long way in easing access to climate index information and informing policies for effective climate change adaptation and mitigation among vulnerable communities across the country. This paper therefore, uses geospatial technologies to develop a spatially explicit tool anchored on climate change hotspot object-based regionalization models for Uganda whilst utilizing the *geon concept* (Lang et al., 2010). This approach adopted by related research (Hagenlocher et al., 2013 and Kienbeger &Hagenlocher 2014) provides not only an iterative but a continuously evolving process of climate resilient pathways to manage change within these complex systems. This in turn avails decomposable deliverables that make sustainable development the ultimate goal in national policy formation and considers mitigation as a way to keep climate change moderate rather than extreme.

## 2. Study Area

Climate change in Uganda has started manifesting itself through increased frequency of extreme weather events, i.e. droughts, floods and landslides, pausing a serious threat to the country's natural resources, social and economic development (NAPA, 2007). This research was therefore carried out within the spatial domain of the Republic of Uganda represented in Figure 1 for spatial delineation of extreme weather and climate change hotspots.

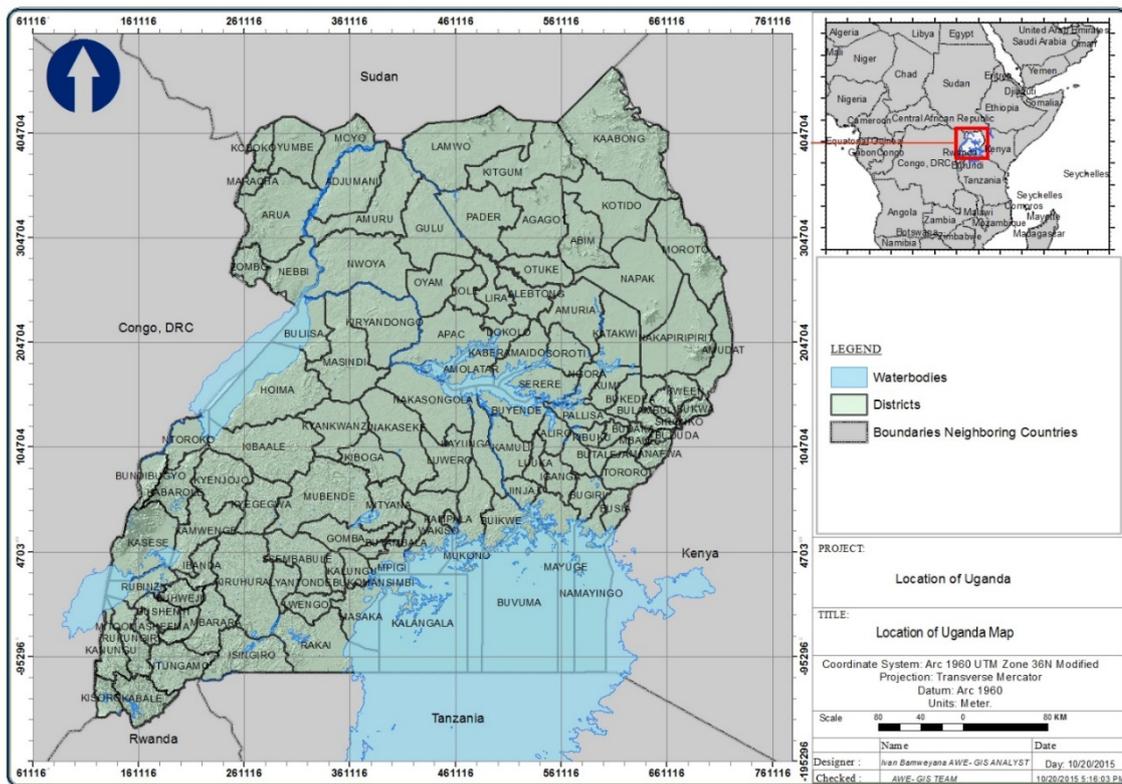


Figure: 1 Location map of Uganda

## 3. Methodology

Spatially explicit climate hotspots are direct derivatives of the integration of proxy multidimensional phenomena. The combination of the different dimensions of phenomena is achieved by applying the spatial composite index formation methodologies (Salzman et al., 2003; Mazziotta and Pareto, 2012). The construction of a composite index is a complex methodological flow based on phases, with each phase involving several alternatives and possibilities that have an effect on the quality and reliability of the results (Mazziotta and Pareto, 2013). Upon development of a theoretical framework and selection of variable, Trogu, (2014) spatialized the Organisation for Economic Co-operation and Development (OECD), (2011) general composite index construction as implied in Table 1. This study adopted the spatial methodology workflow to cope with the geospatial nature of the datasets.

Table: 1 Spatial Index construction workflow

<b>OECD/JRC Methodology</b>	<b>Spatial Methodology</b>
Definition of the theoretical framework Definition and analysis of spatial indicator framework	
Data analysis Multivariate analysis Data normalization	Data modelling and indicator processing Data normalization
Weighting and aggregation Sensitivity analysis Data Visualization	

### 3.1. Spatial Indicator framework

Indicators that relate to extreme climate and weather events, were conceptualized through expert opinion and validated against literature review. Upon conceptualization, identified indicators were obtained from data custodian organizations that include; Uganda meteorological services, climatology analysis software like GeoClim of USGS/ FEWSNET (Famine early warning systems network), and DFO (Dartmouth flood inventory). Ideally, the indicators were adopted relative to their relevance, temporal scale, spatial scale, accessibility and soundness. Consequently, an indicator framework for extreme climate and weather events was developed (Table 2). The indicators with their respective proxies were evaluated and detailed in the same table. The framework is inclusive of indicators that had sufficient data over the cumulative time series subject to validation. The indicators also give the best spatial representation across the study area.

Table: 2 Extreme weather and climate events indicators and sources

<i>Dataset</i>	<i>Proxy</i>	<i>Available time series</i>	<i>Source</i>
Temperature	Temperature	1981-2015	UMA,USGS/FEWSNET-GeoCLIM
Precipitation	Average rainfall	1981-2014	UMA,USGS/FEWSNET-GeoCLIM
	Co-efficient of variation of rainfall	1981-2014	UMA,USGS/FEWSNET-GeoCLIM
Drought	Standardized Precipitation Index(SPI)	1992,1997, 2002	USGS/FEWSNET -GeoCLIM
Flood events	Flood frequency	1961-2015	UNEP/DFO

### 3.2. Data Modelling and Indicator Processing

#### 3.2.1. Data processing

Precipitation related data was generated with aid from the GeoClim Climatology analysis tool. GeoClim is a tool that facilitates climatological analysis of rainfall and temperature data developed by United States Agency for International Development (USAID), United States Geological Survey (USGS) / (FEWS NET). GeoClim runs with climate Hazards Group Infra-Red Precipitation with (Station) (CHIRPS) data. The station data is added after calibration using in-situ / station data. The tool builds on approaches of ‘smart’ interpolation techniques, high resolution, and long period of record precipitation estimates based on infrared Cold Cloud Duration (CCD) observations.

The CHIRPS GeoClim tool comes with BASIICS (Background-Assisted Station Interpolation for Improved Climate Surfaces) component algorithm. The algorithm was used to blend the gridded datasets (CHIRP satellite data) with the station data obtained from the Uganda Meteorological Authority (UMA). The blending is done using a modified inverse distance weighting (IDW) approach that borrows from the concepts of kriging. The algorithm extracts values from the grid at all locations where the ground station data has valid values. The program then carries out least squares regression between the collocated point and the extracted grid values. It then outputs the R-squared ( $R^2$ ) value in a statistical diagnostic file. The resultant satisfactory calibration product (CHIRPS) was then interrogated and rainfall, co-efficient of variation of rainfall, temperature and drought (SPI) proxy data generated. The already pre-processed flood data is generated by DFO. It is derived from news, government, institutional, and various remote sensing sources like Landsat and MODIS.

#### 3.2.2. Indicator Pre-Processing

In order to facilitate further analysis, images must have similar properties such as; spatial extent, coordinate system and pixel size. To achieve this, the data obtained was subjected to conversion, resampling and aggregation, interpolating and transforming surface processes as shown in Figure 2.

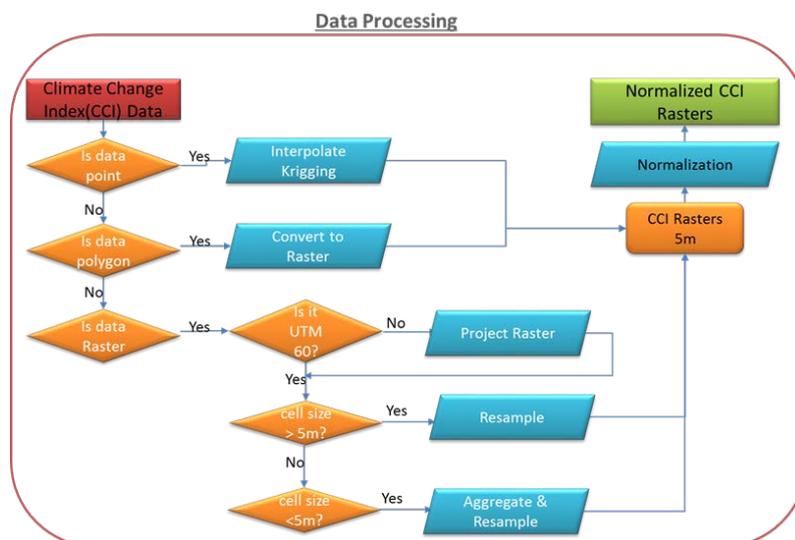


Figure:2 Indicator processing methodology flow chat

### 3.3. Surface Data Normalisation

The identified indicators required normalization to render them comparable. Several normalization techniques exist for example, ranking, min-max transformation, and standardization (Freudenburg, 2003; Jacobs et al., 2004). However this study adopted the min-max method. This is because the min-max method has the ability to widen the range of indicators lying within a small interval (OECD, 2011) and further preserve relationships within the data.

OECD (2011) handbook on constructing composite indicators details the min-max normalization as; - Each indicator  $x_{qc}^t$  for a generic country  $c$  and time  $t$  is transformed in;

$$I_{qc}^t = \frac{x_{qc}^t - \min_c(x_q^t)}{\max_c(x_q^t) - \min_c(x_q^t)} \dots \dots \dots 1$$

Where  $\min_c(x_q^t)$  and  $\max_c(x_q^t)$  are the minimum and maximum value of  $x_{qc}^t$  across all countries  $c$  at time  $t$ . In this way, the normalized indicators  $I_{qc}$  have values lying between 0 (laggard,  $x_{qc}^t = \min_c(x_q^t)$ ) and 1 (leader,  $x_{qc}^t = \max_c(x_q^t)$ ).

### 3.4. Indicator Mapping

The application of the above techniques resulted into the mapping of temperature (A), Rainfall (B), Flood (C), drought (D) Co-efficient of variation of rainfall (E) as individual indicators represented in Figure 3. The scale is on a continuum of red to green, with red representing the area's most susceptible to extremities of the corresponding weather and climate indicator. The green represents the area's least susceptible to natural extremities of the corresponding weather and climate indicator.

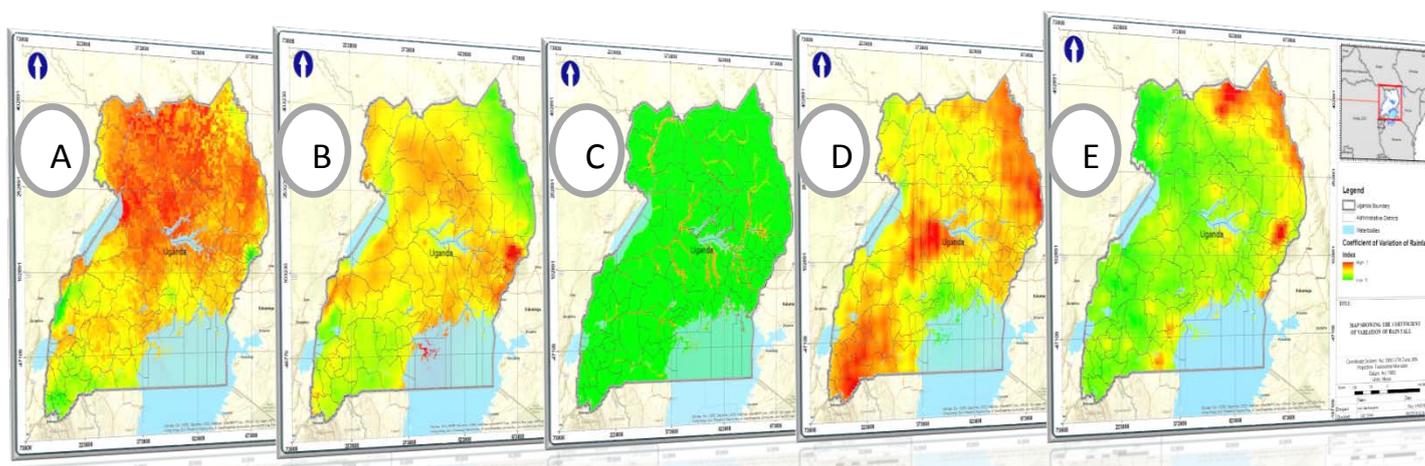


Figure: 3 Mapped extreme weather and climate events indicators

### 3.5. Weighting

This was accomplished using Principle Component Analysis (PCA) as statistical weighting technique due to its ability to group together individual components which are collinear. PCA was carried out and Eigen values and vectors for the input indicators obtained as an ingredient for

obtaining factor loadings in factor analysis. Table 3 shows the results from PCA based on factor analysis rotation matrix obtained using the varimax rotation method.

The rotation covered eleven iterations. The rotation involved re-distributing the values' commonalities so that a clearer pattern of loadings emerges. The idea was to find an arrangement in which test values load high on one factor and low on others. In this study, four factors with Eigen values greater than one are observed for extraction, the percentage of variance represents how much of the total variability is accounted for by each of the factors. And also, the rotated sums of the squared loadings accounts for the factors that met the cut- off criterion.

Table: 1 Normalized indicator weight

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings			Normalized Weight
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	
1	1.810	36.200	36.200	1.611	32.220	32.220	1.000
2	1.032	20.648	56.848	1.132	22.645	54.865	0.424
3	1.010	20.198	77.046	1.109	22.186	77.051	0.408
4	.689	13.773	90.820				0.170
5	.459	9.180	100.000				0.000

Results show that factor 1 accounts for 32.220% of the variability in all 5 variables. Factor 2 accounts for 22.645%, factor 3 accounts for 22.186%. Thus the first three factors account for 77.051% of the total variance.

The loadings through a rotated component matrix obtained show that the first principal component were heavily loaded on rain and drought, the second component loaded on temperature and coefficient of variation of rainfall and the third component loaded on the flood as shown in Table 4

Table 4 The rotated component matrix indicating the actor loadings for each indicator

Rotated Component Matrix			
	Component		
	1	2	3
Temperature	.465	.470	-.420
Flood	.019	-.050	.961
Rain	.996	.068	.022
Drought	.928	-.053	-.062
Coefficient of variation of rainfall	-.021	.949	-.069
Indicator Weight	1.000	0.424	0.408

### 3.6. Multi Criteria Decision Analysis (MCDA)

With the weights for the sub indicators determined through principal component analysis, the weighted linear combination (WLC) was adopted to aggregate the spatial variables for the subsequent calculation of the CCCI. This approach multiplies normalized criteria scores by relative criteria weights for each sub indicator (Geldermann & Rentz 2007; Nyerges & Jankowski 2010). Drobne et al., (2009) further guides that the total score is obtained by multiplying the importance weight (w) assigned to each sub indicator (x) by the scaled value given for that into the alternative and then summing the products over all sub indicators(S) as indicated in Formula  $S=w_i x_i \dots\dots\dots 2$

$$S = \sum w_i x_i \dots\dots\dots 3$$

The Formula  $S=w_i x_i \dots\dots\dots 2$ : achieves the data integration of the CCCI hotspot in an object based image analysis (OBIA) environment. However there was need for concepts adding value to these strands of data by extracting meaningful information (Lang et al, 2010). To address this challenge, Kienbeeger et al. (2008), proposes the adopted geon concept; a generic concept to reduce complexity on successive levels of intervention. For each unit, an index of cumulative climate change (CCCI) was calculated. Any given delineated object with cumulative sub indicators ( $s_1 \dots\dots\dots s_5$ ) had the CCCI calculated and the magnitude of the resulting vector output in a multidimensional space as;-

$$|CCCI| = \sqrt{s_1 + s_2 + s_3 + s_4 + s_5 \dots\dots\dots 4}$$

The final vector value depicts the distance and position of each unit within the feature space. This reflects the notion of the regionalization. The result vector was mapped as shown in Figure 4 to represent decomposable extreme weather and climate events hotspots for Uganda

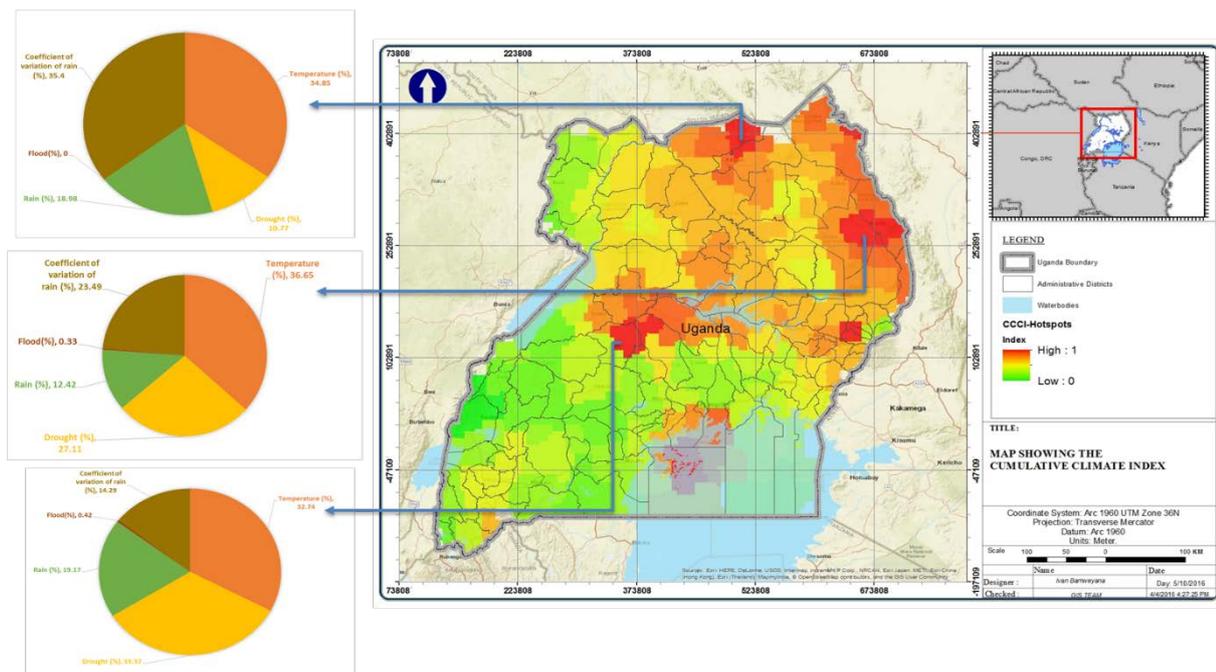


Figure: 4 Unit based cumulative national extreme weather and climate hotspots

### 3.7. Sensitivity Analysis

Whereas these Spatial composite indicators are increasingly being used for bench-making countries performances (Saisana & Tarantola 2002), there are doubts often raised about the robustness of the resulting index rankings and about the significance to the associated policy message (Saisana et al, 2004). In this case, sensitivity analysis was undertaken to assess the robustness of the composite indicator in terms of; mechanism for including or excluding an indicator, the normalization scheme, the imputation of missing data, the choice of weights and the aggregation method (OECD, 2011).

Variance based methods of sensitivity analysis have assessed themselves as versatile and effective among the various available techniques for sensitivity analysis of model output (Annoni et al., 2010). Unlike experimental weighting, where the effects of factors are over estimated, variance based methods look at the entire factors distribution, using customarily Monte Carlo methods of various sophistication (Archer et al., 1997). Annoni et al., (2010) further asserts that the number of terms in the analysis of variances (ANOVA) decomposition of the variance of a model  $k$  grows as  $2^k$ . This makes it customary to compute just two sets of index; the  $k$  ‘first order’ and  $k$  ‘total’ effects (Saltelli et al., 1999). According to Annoni et al., (2010), for a given model of the form  $y = f(x_1, x_2, \dots, x_k)$ , with  $y$  a scalar, a variance based first order effect for a generic factor  $x_i$  can be written as;-

$$v_{x_i}(E_{x_{\sim i}}(y|x_i)) \dots\dots\dots 5:0$$

Where  $x_i$  is the  $i$ -th factor and  $x_{\sim i}$  denotes the matrix of all factors but  $x_i$ . The meaning of the inner expectation operator is that the mean of  $y$  is taken over all possible values of  $x_{\sim i}$  while keeping  $x_i$ . The associated sensitivity measure (first order sensitivity co-efficient) written as:

$$S_i = \frac{v_{x_i}(E_{x_{\sim i}}(y|x_i))}{v(y)} \dots\dots\dots 5:1$$

Where  $v(y) = v_{x_i}(E_{x_{\sim i}}(y|x_i)) + E_{x_i}(v_{x_{\sim i}}(y|x_i)) \dots\dots\dots 5:2$

$s_i$  is a normalized index, as  $v_{x_i}(E_{x_{\sim i}}(y|x_i))$  varies between zero and  $v(y)$ .  $v_{x_i}(E_{x_{\sim i}}(y|x_i))$  measures the first order (e.g. additive) effect of  $x_i$  on the model output, while  $E_{x_i}(v_{x_{\sim i}}(y|x_i))$  is customarily called the residual.

The total effect order variance based measure is the total effect in index:

$$S_{Ti} = \frac{E_{x_{\sim i}}(v_{x_i}(y|x_{\sim i}))}{v(y)} = 1 - \frac{v_{x_{\sim i}}(E_{x_i}(y|x_{\sim i}))}{v(y)} \dots\dots\dots 5:3$$

$S_{Ti}$  Measures the total effect, i.e. first and higher order effects (interactions) of factor  $x_i$ . One way to visualize this is by considering that  $v_{x_{\sim i}}(E_{x_i}(y|x_{\sim i}))$  is the first order effect of  $x_{\sim i}$ , so that  $v(y)$  minus  $v_{x_{\sim i}}(E_{x_i}(y|x_{\sim i}))$  give the contribution in of all terms in the variance decomposition which include  $x_i$ . This qualitatively determines the indicators that have the most influence on site ranking .This accounts for the rank robustness of the climate change hotspot model.

The indicators were each subjected to a minimum weight string of 0.01 and a maximum weight string of 0.9 and run through ten thousand (10,000) Monte Carlo simulations. Consequently the global sensitivity analysis average shift in ranks indices  $S$  ‘first order’ and  $ST$  ‘total effect’ were extracted

as shown in Table 5. Table.5 presents the GSA results in percentile format. The first order sensitivity index (s) represents for indicators that, if fixed independently, would reduce the variance shift in ranks most. This accounts for influence of indicators. The total effect index (ST) represents the significance of the indicators to the composite.

Table 5; Global sensitivity analysis percentile influence and significance

<b>Factor</b>	<b>%S</b>	<b>%ST</b>
Drought	40.7	44.5
Temperature	14.7	11.9
Mean_Rain	13.3	16.3
Mean_Flood	9	8.1
Mean_Cov_Rain	13.6	19.2
NONL	9.7	

## **4. Results and Discussion**

### **4.1. Static extreme weather and climate events hotspot Identification**

The result hotspot map was mapped as shown in Figure 4 to represent decomposable extreme weather and climate events hotspots for Uganda .Areas that are highly susceptible to extreme climate and weather events are indicated on the continuum of red to green. Red represents the most susceptible (hot spots) and thins down to green which represents the less susceptible (cold spots). In general, Figure 4 shows high CCCI hotspot values in the administrative regions of Eastern Uganda, south western Uganda, parts of western central and the far north. Furthermore, homogenous units of weather and climate extremes were explored and their sub-indicators decomposed into their percentile contribution to respective units as shown by the pie charts in Figure4

### **4.2. Web Visualisation Tool**

With the emersion of this spatially based extreme weather and climate hotspots static map, open access to the same becomes essential. This visualization tool has been designed to allow for the decomposition of the identified hotspots into their underlying sub-indicators and for open access as well as interrogation of extreme weather and climate hotspots data in Uganda as shown in Figure 5. The tool was developed using ArcGIS online. It is furnished with abilities to, print visualized output, view individual layer indices independently, analyse and extract the attribute table, ability to change base maps, measure distances and areas, scale, search places and pick the coordinates.

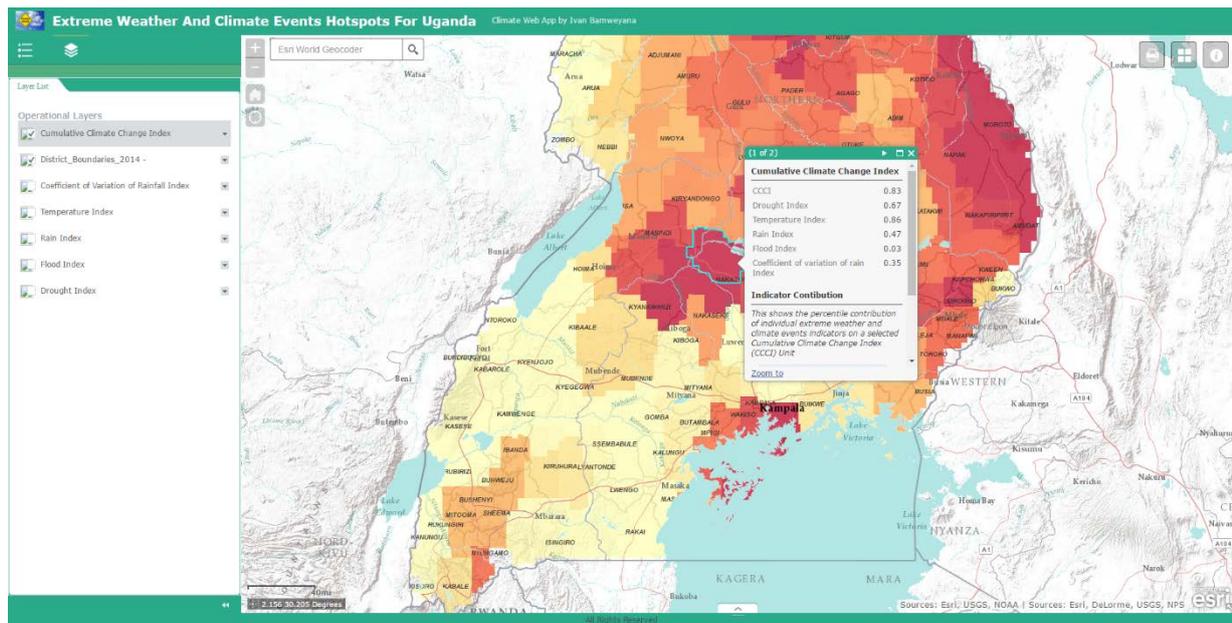


Figure: 5 ArcGIS online based visualization extreme weather and climate events hotspot tool

## 5. Conclusions and Recommendations

This study set out to model decomposable climate change hot spots representing the extreme weather and climate events aggregated in a Cumulative Climate Change Index (CCCI). This was to allow one decompose a given hotspot unit into contributing sub indicators. Conclusively, the modelled national extreme weather and climate events hotspot bring forward a holistic view of decomposable spatially based indicators. The research also provides an additional understanding of the complex interplay of the contributing underlying weather climatic events and their spread in terms of influence and intensity in various regions.

The research recommends to policy makers, to not only decompose the identified hotspots into the underlying sub indicators but also prioritize intervention areas. Additionally, this provides additional information to yield informed policies for effective climate change adaptation procedures to be used in mitigating the impacts among vulnerable communities in the country. To researchers, initiation of this work provides room for time series assessments, this will enable stakeholders monitor spatial shrinkage and expansion of related hotspots. Researchers will so be able to avail projections of future hotspot behaviour under this arrangement.

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