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Modelling Maize Yield Vulnerability to Climate Variability

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Abstract The effect of climate variability on maize yield has been the subject of numerous studies globally, but very few of these studies have focused on the local scale in Africa. As a result, the focus of this work is on creating a vulnerability index that combines sensitivity, exposure, and adaptive capacity to assess the degree of vulnerability of Maize yield to climate variability in the south-south region of Nigeria in West Africa. The ratio between the actual maize yield and the projected yield was used to calculate yield sensitivity. Adaptive capacity examines some of the socioeconomic and demographic factors in the study area. A fuzzy function was employed to derive the aggregation of the determinants of Adaptive Capacity (adult literacy, poverty prevalence, accessibility to the settlements of people, and dependency ratio). Exposure was expressed as the average of the long-term and short-term climatic factors (Rainfall and Temperature). Yield sensitivity ranges between 0.471 to 0.698 with moderate to high sensitivity observed in almost the entire growing region. Exposure values indicate a very high level of climate variability with the North of Edo to the Southeastern and Southwestern parts of the State being more exposed. Adaptive capacity is highly variable ranging from 0.174 to 1. The vulnerability index ranges from 0.393 to 0.698. The result indicates a very high to extremely high vulnerability on maize yield across the majority of growing regions in the south-south, which is an indication of a probable yield drop due to changing climate. This model provides a structure for decision-making and planning on climate variability mitigation needs assessment.

Keywords: Climate Variability; Maize Yield Sensitivity; Exposure Index; Adaptive Capacity; Yield Vulnerability.

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List of Abbreviations

PAR - Pressure and Release Model

SSGPZN – South-South Geopolitical Zones of Nigeria

VUIm – Vulnerability Index of Maize

SEIm – Sensitivity Index of Maize

EXPIm – Exposure Index of Maize

ADCm – Adaptive Capacity of Maize

1. INTRODUCTION

In today's world, the issue of climate variation takes precedence when it comes to agricultural matters, most especially in the aspect of crop production. The risk in the agricultural sector is on the rise due to the strong link of the industry with food security (Martins et al., 2017). With regards to the current trend in climate patterns, researchers have been studying the nature of temperature and rainfall patterns but with more emphasis on the national scale rather than the regional level (Adenuga et al., 2021; Dong et al., 2020; Hussein & Estifanos, 2023; Maxwell et al., 2019). It has been noted that an increase in climate extremes (such as droughts and floods) might lead to a decrease in crop productivity (Malhi et al., 2021; Martins et al., 2017). Climate variability can cause crop loss and threaten food security (Alemu & Mengistu, 2019; Schneider & Asch, 2020). As a result, a change in rainfall patterns may cause water stress, which may then lead to a low-quality crop yield (Brito et al., 2019; Igiehon et al., 2021).

In Nigeria, maize crop production began as a subsistence crop but has progressively risen to a marketable crop, which serves as a chief raw material in many production companies, especially agro-based ones (Iken & Amusa, 2004; Nwokoro et al., 2021). As a result, more study has been done on ways to reduce the effect of climate change on crop productivity. The research by Shi and Tao (2014), on how climate change and variability affects maize yield reported an overall significant effect but a major snag in the research was its failure to capture local peculiarities and their resulting vulnerabilities. Consequently, there exists a need to explore climate variability and identify potentially vulnerable areas across the South-South geopolitical zones in Nigeria.

The level of vulnerability of a system is determined by its sensitivity, exposure, and adaptive capacity response. A crop's sensitivity is dependent on whether it responds positively or negatively to climatic variations (Jägermeyr et al., 2021). In a related study, maize yield sensitivity to climate change in China from 1976 to 2016 was investigated and it was noted that the yield of maize in China was significantly impacted by temperature increase. The study revealed that the yield of Maize was reduced by 5.19 kg 667 m^{-2} (1.7%) for every 1°C rise in

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temperature (Wu et al., 2021). The study demonstrates that although precipitation was also shown to have a favourable impact, the overall effect was minimal, but the temperature had a substantial impact on the increase of maize yield. Ayanlade et al. (2009) also used a Geographic Information System (GIS) to evaluate how crop yields responded to inter-annual variability in rainfall in the middle belt of Nigeria. Major maize-producing areas in Nigeria were selected for the investigation, and rainfall data from the 30 years between 1970 and 2000 were used. Using a GIS database, data on the climate and maize yield were mapped, and Arc-View GIS Interpolation and other geospatial analysis methods were used to map the impacts of rainfall variability on maize production. From the maps created, their findings indicated that inter-annual rainfall variability was what produced differences in the rate of maize yield.

Exposure on the other hand can be seen as the rate at which a particular unit of analysis responds to climate stress. It may be represented as either long-term changes in climate conditions or changes in climate variability, including the magnitude and frequency of extreme events" and this is frequently characterised by a combined effect of stressors like drought and extremely high temperatures (Chimonyo et al., 2019). In an effort to foresee future agroclimatic conditions and their effects on European grasslands, Trnka et al. (2021) demonstrated that by 2050, the south and west European grasslands may be exposed to heat and drought twice as much as they are now, and the area that experiences regular heat and drought will move further north. This thus indicates the necessity to create innovative strategies for preserving grassland productivity to mitigate the consequences of climate change. The effect of climate change on the yield of crops in the Jimma Zone Upper Gilgel Gibe districts of Ethiopia was evaluated and forecasted by Sime and Demissie (2022) under two Representative Concentration Pathways (RCPs), high (RCP8.5) and medium (RCP4.5). While maize and wheat yields were forecast to rise under the RCP8.5 rainfall scenario, teff and sorghum yields were predicted to fall. The minimum temperature increased between 0.38 and 1.83 °C under RCP4.5. Overall, their study showed that variations in temperature will have a greater influence on crop yield than the change in rainfall in the future period of the year 2030–2050.

In a five-year study conducted in Portharcourt from 2005 to 2009, Ropo and Ibraheem (2017) examined the effects of temperature and rainfall (exposure) on the yield of two important crops, cassava, and maize. According to the study, temperature had a negative correlation with the yield of both cassava and maize, indicating that when temperature drops, both cassava and maize yields rise. They emphasised how important minimum temperature is for the development of cassava and maize, as well as how rainfall affects both crops' yields only somewhat, suggesting that excessive rainfall may reduce agricultural yields. Additionally, crop yields' responses to temperatures above a certain point could be detrimental to agricultural productivity (dos Santos et al., 2022). Their study suggested that more research be done on closely similar crops in the study area along with an additional insight into the main impacts of temperature and rainfall on the production of maize and cassava.

High susceptibility and exposure are typically the results of skewed development processes, according to Moulds et al. (2021). They modelled the impact of flood risk management on

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social inequality. Their model showed that a key factor in lowering social inequality and promoting sustainable economic growth is minimising the susceptibility of informal communities to catastrophic occurrences like flooding. Floods, droughts, and severe temperatures are all hazards associated with the climate, but by themselves, they do not become disasters unless they come into contact with a vulnerable scenario. If people are exposed to risks and are unable to appropriately foresee, withstand, and recover from them, they become vulnerable. Richer households might not be as affected by vulnerability as those in poverty, who contribute far more to it. According to the current climate, maize crops in Nigeria are thought to be extremely vulnerable to the effects of major climatic events (droughts and floods) as well as to possible climate change. A valuable model for comprehending and lowering maize production sensitivity to climate disasters is the disaster crunch model as shown in Figure 1. This model follows a cause-and-effect approach and can be used to understand the causes of a disaster (Mahmood & Hamayon, 2021). The model reveals a progression of vulnerability. It starts with underlying social issues that make it difficult to meet people's needs and the translation of root causes by dynamic pressure into unsafe conditions. According to the model, a crunch is more likely to affect vulnerable communities because of the unsafe environments in which they reside.

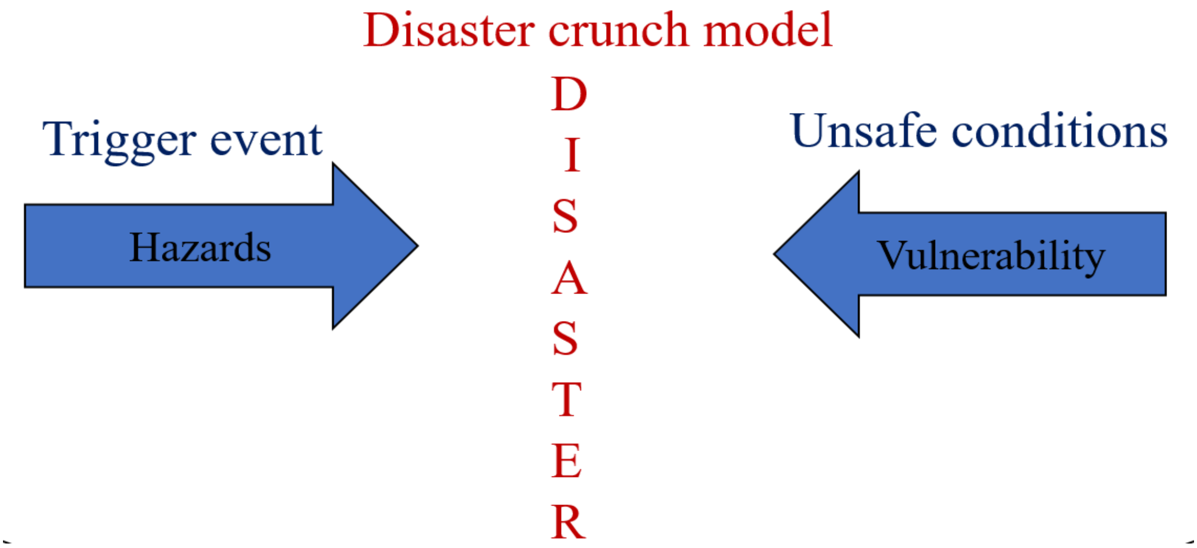

Figure 1 The Disaster Crunch model (Wisner et al., 2004)

The Pressure and Release (PAR) Model as shown in Figure 2 is another model that was utilised in this study to show how structures and processes acting in space and time shape disasters and disasters in the context of this study is adverse climate events. Risk managers would have a framework for assessing vulnerability to disasters and minimising it with a conceptual model similar to the Pressure and Release (PAR) model created by Wisner et al. (2004). According to the PAR model, a disaster happens when there is a collision between two opposing forces which is the force that generates the natural hazard and the processes that cause the vulnerability. The adoption of this model to further explain the concept of vulnerability in this study reflects the understanding that maize yield vulnerability to climate variability is the intersection of two opposed forces: the processes generating vulnerability on the one side, and the physical exposure to specific climatic conditions on the other.

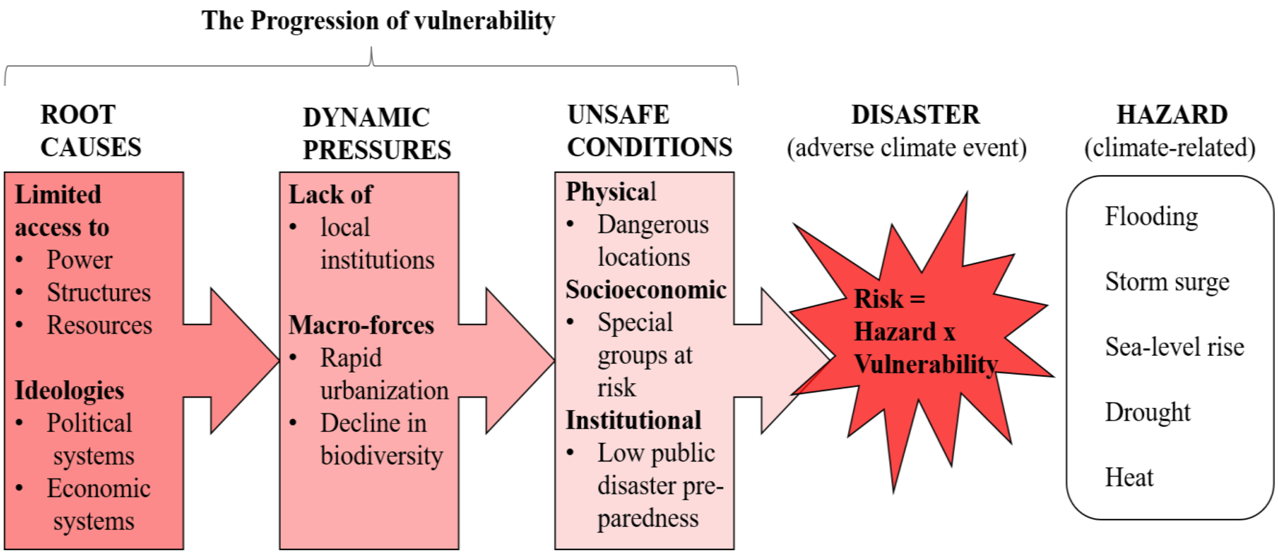

Figure 2: The Pressure and Release (PAR) model (Wisner et al., 2004)

There is general agreement that extreme weather conditions, such as drought, have recognised effects on the yield of crops. However, as observed by Kamali et al. (2018), quantifying crop drought vulnerability is rather challenging since, in most situations, the components of vulnerability are not described in a standardised and spatially comparable quantity but must be established on a fine spatial resolution. To address this problem, they created a physical crop drought vulnerability indicator through the linkage of the drought exposure index (DEI) with the crop sensitivity index (CSI) in sub-Saharan Africa. The difference between precipitation and potential evapotranspiration, as well as the cumulative distribution functions fitted to precipitation, were compared. For periods of one, three, six, nine, and twelve months, DEIs were estimated. Curves were fitted to CSI and DEI relations using a power function, producing various shapes that help to indicate the degree of vulnerability. According to the study, the difference between precipitation and potential evapotranspiration over timescales of one, three, and six months produced the greatest correlation between CSI and DEI. Due to significant water stress, Southern African countries and some areas of the Sahelian strip were particularly vulnerable to drought, but in Central African countries, vulnerability is related to temperature stresses. Their methodology provides further information on ways of assessing various levels of vulnerabilities and their underlying causes. Additionally, their methodology can be applicable also in the case of different regions and at various geographical scales, including the area under study.

A system's adaptive capacity is determined by how well it can respond to climate variability and change. Enhancing adaptive capacity is a technique to reduce vulnerabilities and promote sustainable development. ADC has been reported to be subject to aspects including affluence, literacy, dependency ratio, technology, information, skills, infrastructure, access to resources, management capacities, etc (Dumenu & Takam Tiamgne, 2020). These factors are highly connected that a major setback in any one can reduce the overall ability of the system to adapt (Jia et al., 2021; Vallury et al., 2022). The capacity to read and write, as well as linguistic abilities, considerably improve access to information, which is crucial during disasters. A literate populace would be better equipped to demand a more accountable and efficient administration since they would be more aware of their civil and political rights. Governments are more likely to address vulnerability in areas where such rights exist because they will be held responsible for lessening the effects of disasters (Khan & Salman, 2012). Poverty is a great determinant of vulnerability (Maganga et al., 2021). In this context, poverty is not measured by financial assets but rather by material, as income poverty is inadequate to address multiple forms of poverty. Income depicts poverty rates that are higher than reality because not all households can transform income into wealth (Moulds et al., 2021). Therefore, a high level of poverty may prevent farmers from investing in novel cultivars, drought-resistant maize seeds, fertilisers, and other farm inputs, which would lead to a low capacity for adaptation. People who live in urban areas are less at risk from climate variability than those who live in rural areas because they have better access to resources, such as information and off-farm employment opportunities, inputs, and markets for their farm products. This makes it easier for them to adapt to the effects of climate variability. More responsibilities will fall on the earning members of households with a larger dependency ratio, decreasing their ability to adjust to shocks of all kinds, including climatic shocks (Mesfin et al., 2020). Therefore, a comprehensive evaluation of the literature on ADC and urban vulnerability as well as the availability of data was used to develop the choice of ADC determinants in this study.

Abdollahzadeh et al. (2023) investigated the socio-cognitive aspects of Iran's agricultural systems' capacity for climate change adaptation. Their study identified some factors that serve as a determinant to successful climate change adaptation and such factors include: the awareness and viewpoint of an individual to risks associated with climate, the individual's knowledge about climate and related issues, and the physical accessibility of the individual. They concluded by emphasizing the need for resilience-building initiatives. Their findings could serve as an insight for agricultural authorities to identify the elements and factors that should be given priority to reduce the threat that climate change poses to farming systems. Maldonado-Méndez et al. (2022) taking a slightly different approach, used theories about social capital as an indication for defining and assessing adaptive capacity. They proposed that "social capital" provides a lens to examine how social networks and norms co-evolve to produce farmers' capacity to adjust in the face of social or climatic incidents. Networks and trust are the most common social capital indicators, which can be seen in a variety of situations. The size of a person's social network reflects the strength of their social capital (Choo & Yoon, 2022). The study by Bedeke (2023) reveals that farmers' perspectives on climate change are frequently influenced by their long-term knowledge and experience with extreme weather events that can harm their livelihoods, although the effects of climate variability on farmers' livelihoods are less clear because farmers are active 'agents' and not passive players who are limited by the information and resources that are available to them (Cairns et al., 2013).

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Farmers have evolved coping mechanisms over time to protect themselves from uncertainties (Bedeke, 2023). Sesana et al. (2020) noted that to mitigate farmers' vulnerability to present climatic changes, they must have access to information as well as enough resources.

Efforts towards attaining sustainable economic growth and food security in Africa are becoming more jeopardised by the negative consequences of climatic variability. Therefore, Derbile et al. (2022) aimed to evaluate the consequences of a climate change adaptation plan as well as the sensitivity of some individual crops in Ghana's Upper West Region to climate extremes. According to their findings, maize, and rice were the crops that were most susceptible to drought. They concluded that Climate Smart Agriculture (CSA) efforts should be promoted if rural livelihoods in Ghana and SSA as a whole are to be safeguarded.

In the southwestern region of Uganda, a study by Epule and New (2019) detailed the vulnerability of six important crops, including maize, to fluctuations in growing season precipitation at both the national and regional levels. According to their research, maize had the second-lowest risk index of any crop at the national level, at 33%, while it had the second-highest vulnerability index at the regional level, at 90%. This goes on to show that there is a huge disparity between what is obtained at the national level and the regional level. Many studies which tend to assess crop vulnerability to climate variability focus more on the national level but the research by Epule and New (2019) goes on to indicate that more specific studies such as those obtained at the regional level may be able to give more detailed information about local realities in the field compared to studies at the national scale and thus the essence of this study.

There are actions to mitigate the impact of climate variability on Maize yield and agricultural production impacts at different levels, though the major pressing issue is the inadequate information on climate variability at the regional and local scale. This has therefore hindered decision-making and planning at these levels. As a result, there exists the need to conduct more studies on yield vulnerability, especially of maize, and also make data available for utilization by stakeholders at different levels, given that fluctuations in precipitation, temperature, poverty, and literacy rates could cause a deviation in results at various levels. Therefore, this study emphasizes the significance of detailed investigations of key regions to understand the climatic trends and patterns to propose sustainable adaptation measures.

2. MATERIALS AND METHODS

2.1 Study Area

Nigeria is a cosmopolitan nation with 36 states. Based on variables including cultures, ethnic mix, and shared history, these states are split into six geo-political zones: North Central, North East, North West, South East, South-South, and South West (Chiaka et al., 2022). This study is focused on the South-South Geopolitical zones of Nigeria (SSGPZN) (Figure 3), which is one of the six geographically situated zones within the Niger Delta region of the country. Nigeria is a nation endowed with significant oil reserves and three states, including Bayelsa, Delta, and Rivers, constituted in this study areas, are the primary regions responsible for oil production in the Niger Delta. The region offers diverse opportunities, especially in the agricultural sector. The Niger Delta region is characterized by its substantial agricultural land, freshwater resources, forests, and fauna. The geographical area is home to the world's third-largest wetlands and Africa's largest mangrove swamps, which provide habitats for a diverse range of plant and animal species. The wetlands in question provides a conducive environment for the cultivation of various cash crops, including rubber, cocoa, oil palm, and coconut. Additionally, they also support the growth of staple food crops such as cassava, yam, and plantain (Babatunde, 2020). The geographical area encounters a humid tropical climate, distinguished by alternating wet and dry seasons. Additionally, it comprises a significant proportion of Nigeria's population (Ukhurebor & Siloko, 2020).

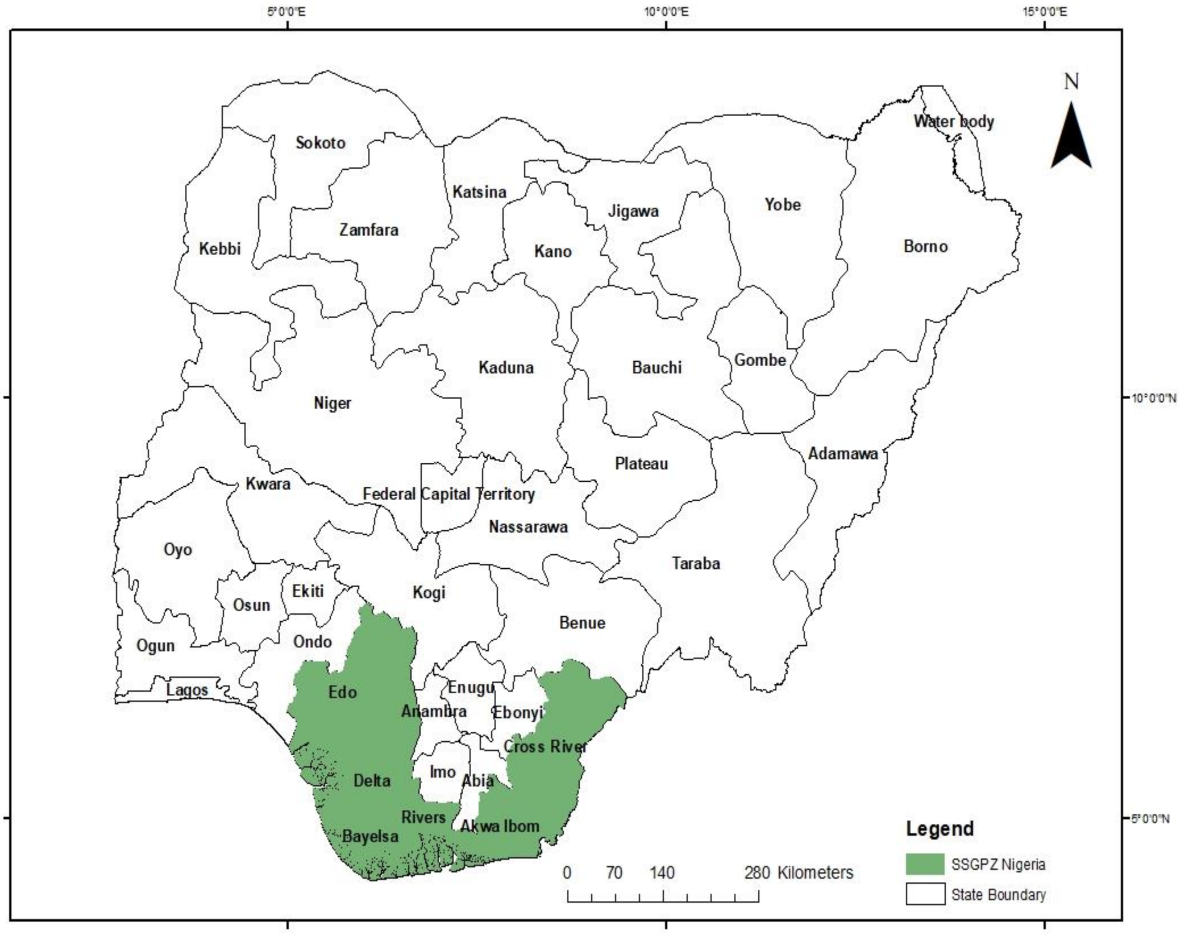

Figure 3 Map of Nigeria showing the SSGPZN

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2.2 Data

The research design adopted for this study is a correlational design. This method was adopted because the research aims to assess relationships among variables, and also involves the repeated observations of variables over a length of time. In the context of this study, the vulnerability of Maize yield is expressed as a function of yield sensitivity and exposure index, adaptive capacity inclusive to determine the extent to which climate variability also impacts Maize producers or growers in the system.

Thus, the Vulnerability Index of maize yield (VUIm) is expressed as the function of:

a) Sensitivity Index of maize yield to climate change (SEIm)
b) Exposure Index of maize yield to climate change (EXPIm)
c) Adaptive capacity (ADCm) of people within the system (the extent to which people in the system can absorb shock).

This is mathematically represented as shown in the equation below

VUIm = SEIm + EXPIm – ADCm ………………………….(i)

2.2.1 Maize Yield Sensitivity Index

Maize yield sensitivity data for Nigeria was sourced from Mendeley Data (Lawal, 2019b) covering 2002 to 2010 with a concentration on the region of interest which is the south-south Geo-political zones of Nigeria (SSGPZN).

2.2.2 Exposure Index

In this framework of the study, factors considered to have an impact on the production of maize are temperature and rainfall. These two climatic parameters were used to assess the degree to which *Maize is impacted by climatic changes and data used for the computation was obtained from Mendeley Data (Lawal, 2019a).*

2.2.3 Adaptive Capacity Index

Adaptive capacity determinants (Stage 1)

Due to data constraints, this study concentrated on adult literacy, poverty prevalence, accessibility to the settlement of people, and dependency ratio as indicators of adaptive capacity. Therefore, a comprehensive evaluation of the literature on ADC and urban vulnerability as well as the availability of data was used to develop the choice of ADC determinants. Poverty prevalence data was obtained from (Tatem et al., 2013), literacy data from (Bosco et al., 2017) dependency ratio data from (Lawal, 2017), and accessibility data from (Linard et al., 2012).

2.3 Methods

2.3.1 Maize Yield Sensitivity Index

The data set which consists of Maize yield sensitivity was created following the method adopted by (Lawal & Adesope, 2019; Shi & Tao, 2014) which incorporates the detrending (multiplicative detrending method) of the yield data. The projected yield for each year was determined by detrending (multiplicative detrending method) the yield data. Detrending's main goal was to help eliminate non-climatic factors that could lead to distortions, such as modifications of crop management techniques, the adoption of new cultivars, etc (Maharjan & Joshi, 2013). The projected Maize yield computed after detrending was divided by the actual Maize yield for the same period to get the maize sensitivity index value. With the aid of ArcGIS Software (ESRI, 2017), the sensitivity raster data sets were merged with the region boundary shapefile to produce the raster image for yield sensitivity, and re-sampling was done to 1km resolution. The essence of the resampling is to make the cell resolution the same.

2.3.2 Exposure Index

Data for the two indices (temperature and rainfall) as obtained from Mendeley Data (Lawal, 2019a) was computed as described by (Lawal & Adesope, 2019). The growing season for maize in the south is from March to August. The average growing season over the long term covers the years 1941 to 2015, while the average growing season over the short term covers the years 1961 to 2015. Following the computation of the exposure index, which is obtained as a ratio of the long-term to the short-term averages, the averages for the specific growing season of maize for the region were calculated. The combined exposure index was created by adding the two individually calculated indexes. With the ArcGIS Software (ESRI, 2017), a raster map was generated using the combined exposure index data by merging the raster data with the south-south region shapefile, and resampling was done to a 1km resolution.

2.3.3 Adaptive Capacity Index

Standardization and aggregation of the determinants using fuzzy logic (Stage 2)

The first step called standardization must be done before fuzzy aggregation can take place and this entails the standardization of each determinant to a fuzzy membership value of between 0 and 1. Fuzzy small was employed to standardise the determinants since it provides an approximate sense of the determinants' probable range of values. In addition, it also shows how ADC would vary across the range (Araya-Muñoz et al., 2016). After standardization, the adult literacy range between 0.2 and 1, the poverty prevalence range between 0.285 to 1, the accessibility range between 0.192 to 1, and the dependency ratio between 0.801 to 1. After assigning the membership values to each determinant, the “GAMMA” function which is one of the fuzzy overlay functions in the ArcGIS Software (ESRI, 2017) was used for the process of aggregation i.e. to combine the fuzzy membership rasters data to form the ADC index map. The GAMMA function tends to be the most suitable in situations where multiple inputs are to be taken into consideration unlike Fuzzy “OR” and Fuzzy “AND”. It does not just return the

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value of a single membership set, nor does it provide more weight to a single variable as Fuzzy "SUM" and Fuzzy "PRODUCT" do. The use of the “GAMMA” function is important as the assessment of ADC deals with the combination of factors rather than just a single factor. Thus, Lewis et al. (2014) as explained by Araya-Muñoz et al. (2016) demonstrate that the "GAMMA" function gives the optimal combination of evidence, whereas other overlay approaches overemphasised single variables at a given position while underplaying others.

2.3.4 Vulnerability Index

Thereafter, the second level of aggregation was done to generate the vulnerability index map by integrating the membership rasters (sensitivity and exposure less adaptive capacity) data using map algebra which is an ArcGIS software tool. Figure 4 Summarises procedures for obtaining the vulnerability Index.

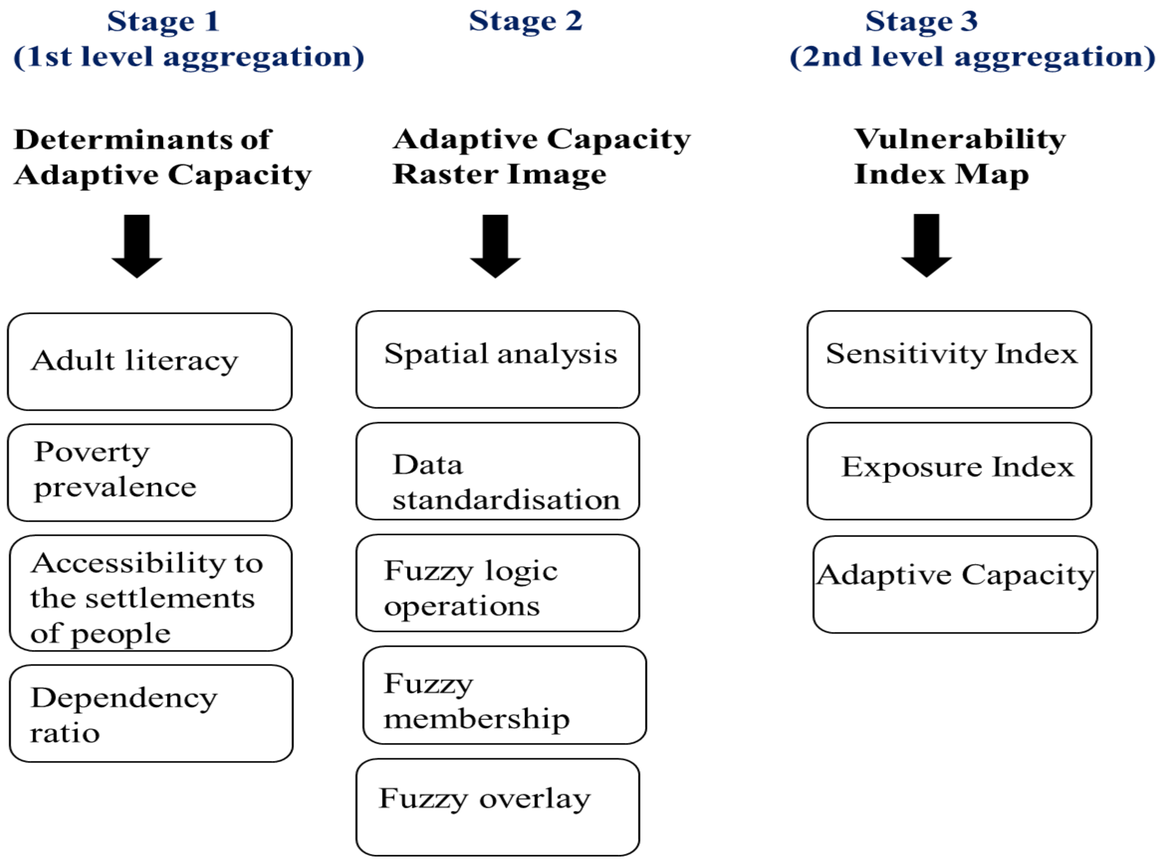

Figure 4 Conceptual Framework for the Standardisation and Aggregation of ADC Determinants using Fuzzy Logic

3. RESULTS AND DISCUSSION

3.1 Maize Yield Sensitivity

The Sensitivity Index (SEI) as shown in Figure 5, indicates a wide variation across the region. The figure shows maize yield sensitivity patterns across the growing areas between the period 2002 to 2010. Three classes were defined using Jenk's classification. With an index ranging from 0.471 to 0.698, a mean value of 0.628, and a Standard Deviation (SD) value of 0.094, the three classes were named low, medium, and high. The low, medium and high as shown on the map legend (Figure 5) indicates the corresponding degrees of Maize yield sensitivity in the areas. The low class has a value of 0.471, which occupies about 27% of the total study area. This could be found extending from the Northeastern part of Edo State to the Southwestern part of Delta State. The medium class has values ranging between 0.471 to 0.576, which occupies about 33% of the study area. This could be found extending from the Northwestern part of Edo State to the South-eastern part of Delta State. This also covers the North-western part of Crossriver. The high class has values ranging between 0.576 to 0.698. This occupies about 40% of the total study area, which could be found extending from the South of Edo, covering almost the entire part of Delta excluding the North-eastern and North-western parts of the State. This extends to Bayelsa, Rivers, Akwa-Ibom, and Cross River, excluding the North-western part of Crossriver State. Patches of this could also be seen in Edo State's northern region. From Figure 5, it can thus be deduced that most of the growing areas have medium to high sensitivities which is an indication of very high to extremely high vulnerability. This is in line with a previous study by Epule and New (2019) that sensitivity increases with vulnerability, and vulnerability could rise with poor yield, which could then result in hunger and food insecurity in the area of focus. Hence the need to determine the pattern of sensitivity for mitigation measures to be put in place, as Maize is one of the major food crops in the country and also in the area where this study is focused.

3.2 Exposure

Figure 6 shows the maize yield exposure index patterns across the growing areas between 1941 to 2015. Using a similar scheme, three classes were defined. The index ranges between 0.393 to 1 with a mean value of 0.757 and an SD value of 0.208. The three classes were named low, medium, and high. The low, medium and high as shown on the map legend (Figure 6) indicates the corresponding degrees of Maize yield exposure to climate variability in the areas. With the aid of ArcGIS, graduated colour symbology was used to show the quantitative difference between mapped features. The classification scheme has three classes, therefore three different colour symbols were assigned and this is an effective way of representing the differences in the magnitude of the phenomenon as this made it easy to distinguish colour variations.

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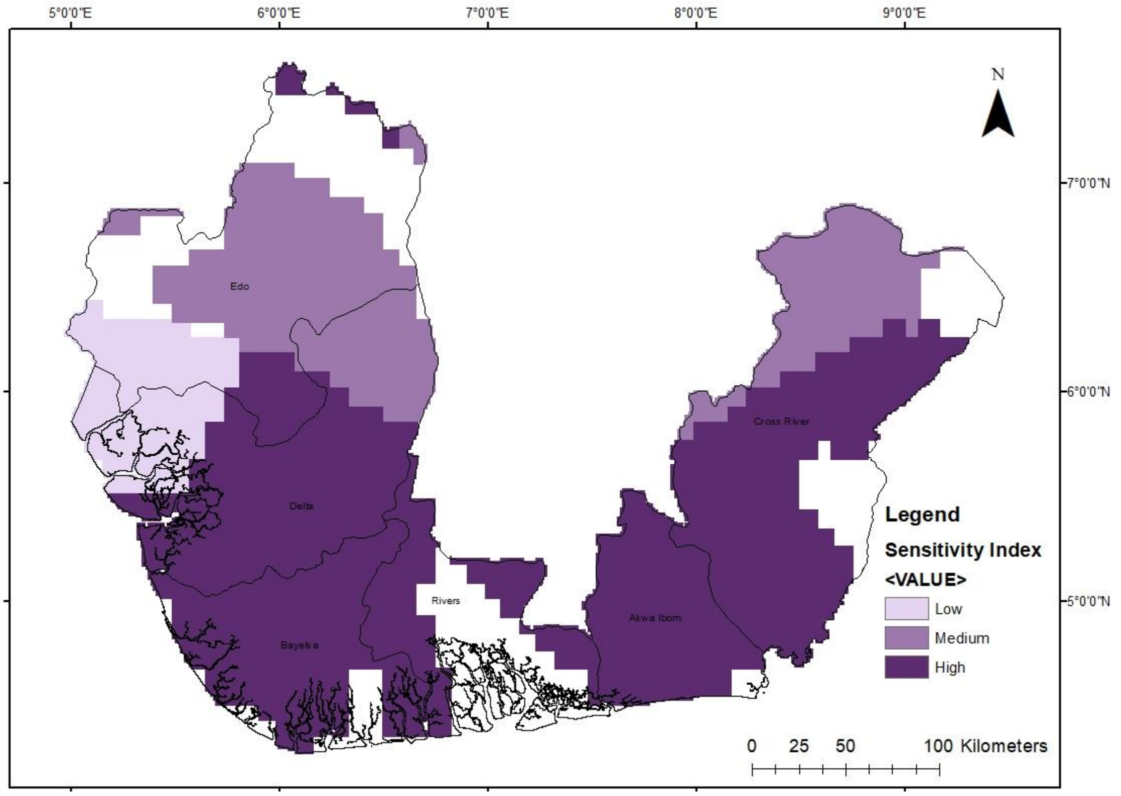

Figure 5 Maize yield sensitivity pattern across growing areas in the SSGPZN

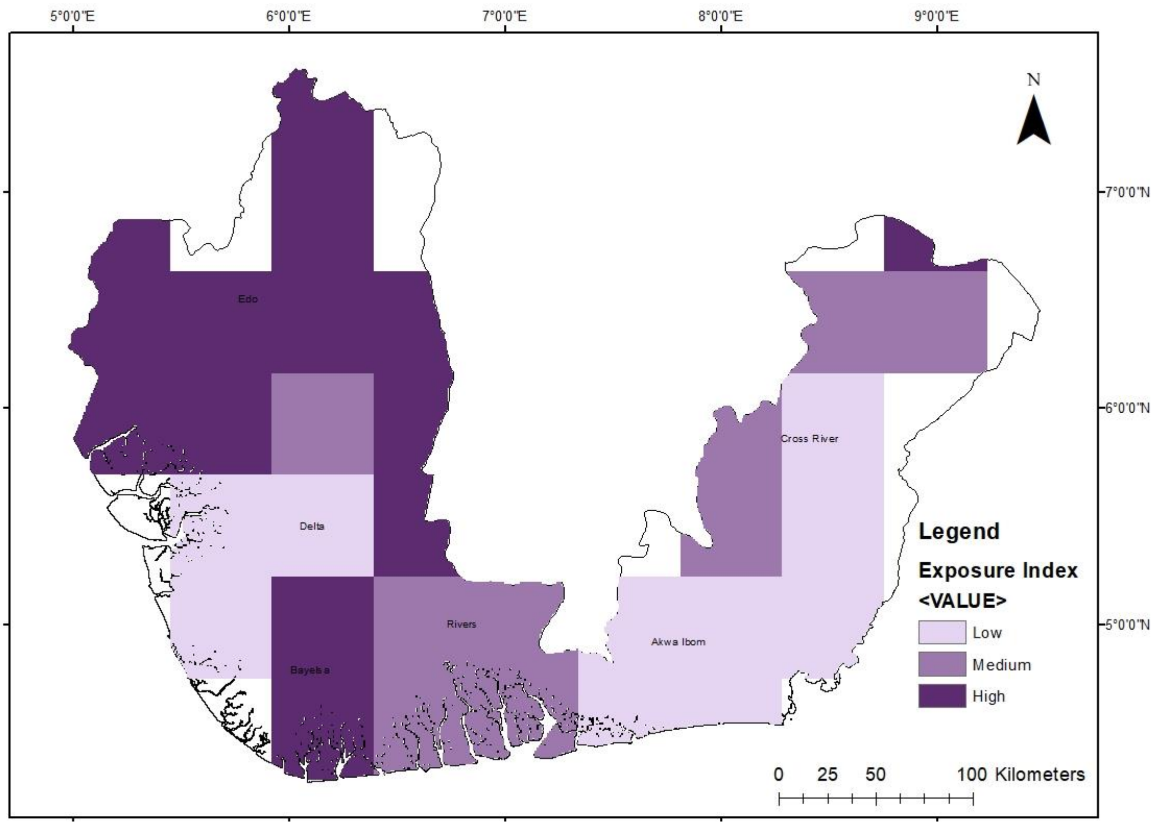

Figure 6 Pattern of Maize yield exposure across growing areas in the SSGPZN

The low class has values ranging between 0.393 to 0.586, which occupies 24% of the total study area. This could be found covering the Eastern part of Delta State, extending to the Southwestern part of the State. This low-class range was likewise found extending from the Southeastern part of Rivers State to the Southeastern and Southwestern parts of Akwa Ibom and extending to the Southeastern part of Cross River. The medium class has values ranging between 0.586 to 0.807, which occupies 34% of the total study area. This could be found extending from the South of Edo to the Northeastern part of Delta. This medium class range could also be found in Rivers State, similarly, in the Northeastern part of Cross River and the Southwestern part of the State. The high class has values ranging between 0.807 to 1, which occupies 42% of the total study area. This could be found spanning from the North of Edo to the Southeastern and Southwestern parts of the State. This extends to the Northeastern part of Delta. This range could also be found in the Northern and Southern parts of Bayelsa state with a small patch in the Northern part of Cross River.

From Figure 6, it can be deduced that areas with high exposure index (EXPI) show high climate variability and vice versa, and a mid-range to high EXPI indicates a very high vulnerability in the majority of the growth zones, which could result in low yield. The work of the following researchers; (Gupta et al., 2020; Masambaya, 2018; Odekunle et al., 2007; Ropo & Ibraheem, 2017; Singhal & Jha, 2021) corresponds to this. Also, Ropo and Ibraheem (2017) revealed that temperature harms the yield of both cassava and maize but a temperature rise could lead to a corresponding rise in the vulnerability of both crops, thus leading to a reduction in crop yield. These results illustrate the crucial function that minimal temperature plays in the development of cassava and maize. There is a need for more efforts to be put in place toward attaining economic growth and food security in Africa. Masambaya (2018), observed that climatic conditions (temperature and rainfall patterns) and extreme weather events have a significant impact on the growth and development of crops. The author highlighted that climate change worsens the exposure of farmers because this tends to generate new and unknown changes in the pattern of rainfall and temperature, including an increased re-occurrence of drought and floods.

3.3 Adaptive Capacity

Also for Adaptive Capacity, three classes were defined using a similar classification scheme and were named low, medium, and high. The low, medium and high as shown on the map legend (Figure 7) indicates the corresponding degrees of adaptive capacity responses of Maize yield. The index ranges between 0.174 to 1 with a mean of 0.806 and an SD of 0.227. Low classes have values ranging between 0.174 to 0.608, which occupies about 25% of the total study area. This could be found covering the central part of Edo extending to Rivers with small patches in Akwa Ibom and Cross River State. Medium classes have values ranging between 0.608 to 0.861, which occupies about 35% of the total study area. This could be found extending from the North of Edo with traces along the East and West of the State and extending towards Bayelsa. Patches of these could also be found in Rivers, Akwa Ibom, and Cross River State. The high class has values ranging between 0.861 to 1, which occupies about 40% of the total study area. This could be found covering the Northeastern part of Edo, extending towards the Southwest down to Bayelsa with traces in Akwa Ibom and occupying a large part of Cross River State.

Figure 7 shows most of the growing areas in the south-south geopolitical zones having low to mid-range ADC thus indicating high to very high vulnerability. Considering the indices used to compute for ADC, the low ADC recorded in the central part of Edo extending to Rivers with small patches in Akwa Ibom and Cross River state could be a result of factors such as poverty. People may be less likely to invest in inputs like fertiliser, high-yielding varieties of drought-resistant maize, and irrigation infrastructure if they are poor (Epule & New, 2019). Literacy level could be a contributor to low ADC as observed in Figure 7. It was reported by Epule and New (2019) that a high poverty level oftentimes translates to a low level of literacy, and often in this situation, the low ADC could also translate to a lack of good road transport networks and technological inputs. Restricted access to financial services could be a contributor to reduced production and then the level of adaptation. The pattern of socioeconomic factors among people varies and this greatly determines their capacity to cope with climate changes.

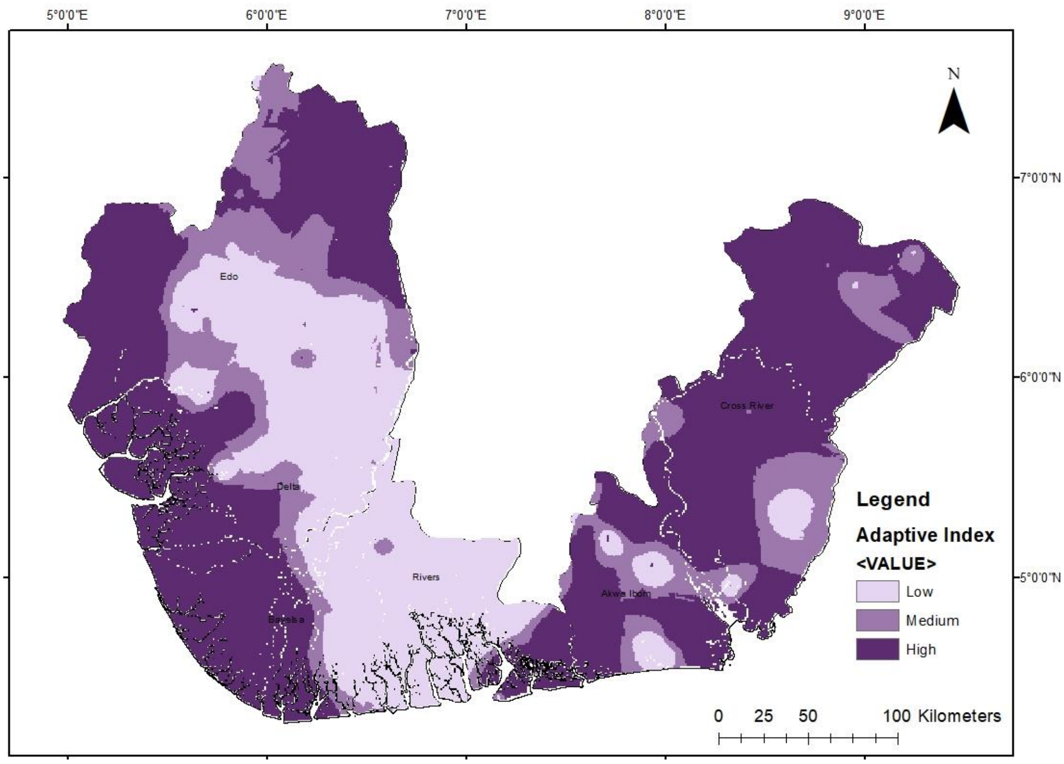

Figure 7 Pattern of adaptive capacity of Maize yield across growing areas in the SSGPZN using selected socio-economic factors

3.4 Vulnerability Index

VUI is a function of the sum of the SEI and EXPI excluding the ADC. Jenk's classification scheme in ArcGIS Software (ESRI, 2017) was used to classify the vulnerability index into three classes. The class ranges between 0.393 to 0.698 with a mean of 0.562 and an SD of 0.092. The three classes were named high, very high, and extremely high following the degree of vulnerability. The high classes range from 0.393 to 0.470, which covers about 27% of the total study area. This occupies the Southeastern part of Cross River. The very high classes range from 0.470 to 0.586, which covers about 33% of the total study area. This occupies the central part of Edo, extending towards the Northeast down to the Southwestern part of the State. Similarly, this range could also be found extending towards the Southwestern part of Delta. This range could also be found in Akwa Ibom, the central part of Cross River, and towards the Northwestern part of the State. The extremely high ranges between 0.586 to 0.698, covering about 40% of the total study area. This could be found extending from the South of Edo towards the Northeastern part of Delta down to Bayelsa. A patch of this could be found in Rivers, Akwa Ibom, and Cross River.

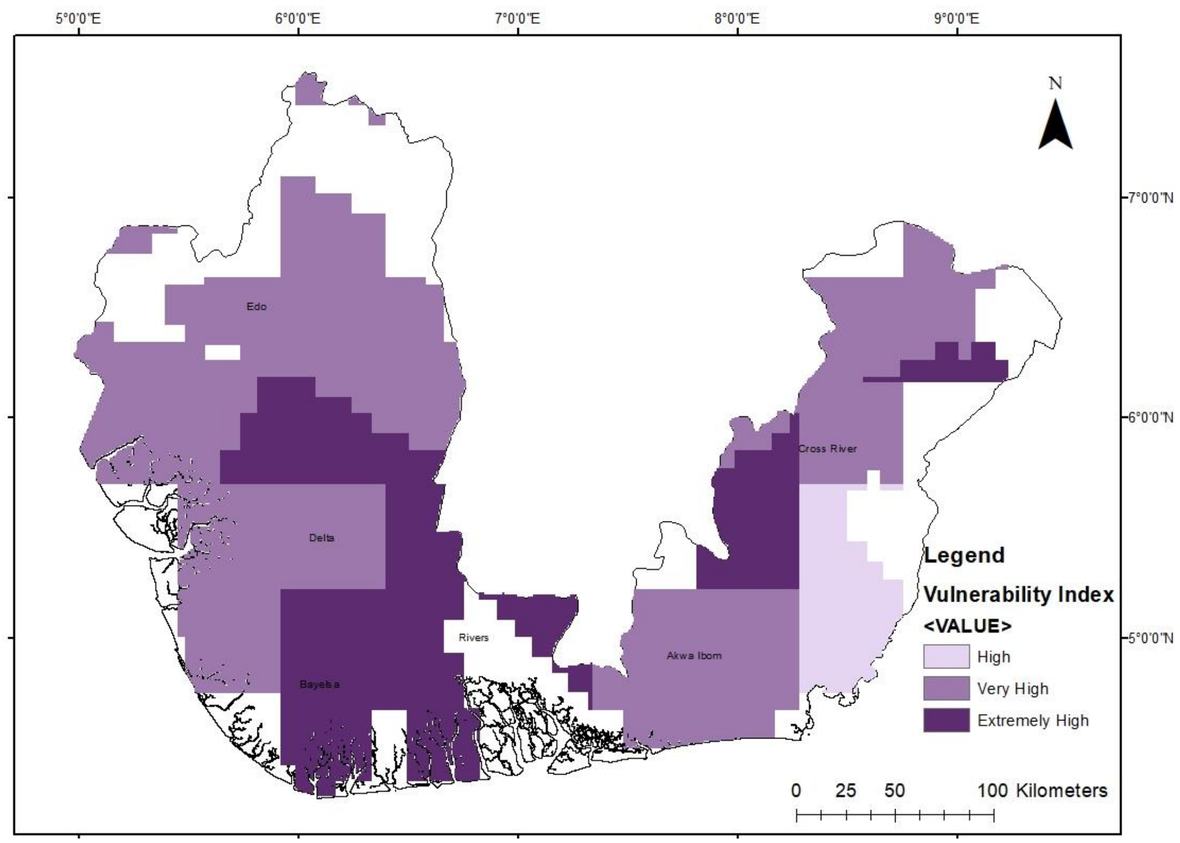

Figure 8 Pattern of Maize yield vulnerability across growing areas in the SSGPZN

The combination of SEI, EXPI, and less ADC gave the YV. From the combination of the indices, most growing areas have very high to extremely high YV which is an indication of the high vulnerability of the yield of Maize in the south-south, to climate variability. Also from the computation, there is an indication that a low sensitivity and exposure results in a low vulnerability as well but this is the opposite for adaptive capacity. This corresponds to a previous research carried out by Epule et al. (2021), which indicates that an increase in sensitivity and exposure leads to an increase in yield vulnerability and vice versa.

The result highlighted where varying levels of yield vulnerabilities could be expected in the SSGPZN for Maize production. This builds on the findings of Ajetomobi (2016) which shows that a 1 % rise in temperature can vary the yield of maize by 4.8%, and the same goes for extreme rainfall which can also cause a 6.33% variability in Maize yield.

4. CONCLUSIONS

Most of the growing areas have a medium to high level of yield sensitivity, which ranges from 0.471 to 0.698. This is an indication of a generally high vulnerability. The growing area is seen also to have a mid-range to high exposure index value of 0.393 to 1, thus indicating a high exposure of Maize to variations in climate. Adaptive capacity value index ranges between 0.174 to 1. Thus indicating that farmers in the south-south geopolitical zones have low to moderately high adaptive capacity, which also indicates a high to very high vulnerability to climate variability. The level of yield vulnerability across the study area is also seen to fall within 0.393 to 0.698, which is a high to extremely high range. Thus, it can be said that climate variability affects maize yield across the study area. Among all the indices, ADC can be said to be the most important. This is because while it is quite impossible to change at the level of farmers, the pattern of future climate, it is, however, possible to devise means on how to respond and cope with shocks by adopting good adaptation measures. The level at which sensitivity and exposure will affect yield and production is largely dependent on good adaptive measures. As a result, this model can be used to identify areas that need to mitigate the effects of climate change on crop productivity.

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