Sustainable Maize CropProduction in Owena Basin

Abstract

To improve maize production, efforts must be doubled to expand the current extent of land suitability profiling. Lingering questionshinged on whether maize is presently grown on land that supports its optimal growth and if farmers'knowledge of their farmland suitability informs their decision to cultivate improved maize varieties. However, attaining the level of food self-subsistence largely requires optimum land use and the adoption of innovative advancement to double farmers' yields. Unfortunately, land suitability profiling and farmers' cultivation of Improved Maize Varieties (IMV) still require more attention in the scheme of initiativesto revitalize agriculture. Previous research addressed other crops rather than maize staples and assessed areas exclusive of the current study area. This paper used the Analytic Hierarchy Process (AHP) to map out land areas suitable for maize cultivation and further used frequency, counts, and parametric estimator to data from 465 maize farmers to profile farmers who cultivated IMV, examine the effect of cultivating IMV and its determinants. Results showed the suitability of AHP for land evaluation, revealing the highly, moderately, marginally, and least suitable areas of land for maize cultivation occupying 5.09%, 56.53%, 37.47%, and 0.89% of the total land. The result also divulges the dominance of old respondents where the age of respondents who did not cultivate IMV ranged between 50 and 61 years while the age of respondents who cultivated IMV ranged between 52 and 72 years. A small-scale production pattern was observed as the area of land under cultivation varied between 1.9 and 2.67 acres for respondents who grew IMV and those who did not. The Potential Outcome mean (Pomean) estimation for respondents who did not grow IMV was 8127.70kg and 11695.8 kg for respondents who cultivatedIMV, and the size of land cultivated and access to extension services significantly (at $P>|z|=0.000$) contributedto the likelihood of farmers growing IMV. The study highlights the importance of harnessing the comparative advantage of land by cultivating the crop it best supports suggesting the need to embrace IMV cultivation and practices including but not limited to the cultivation of legumes to help maintain the soil integrity and further advocate for improved communication between farmers and agricultural services developers.

Keywords: Maize crop, Suitability evaluation, Analytic Hierarchy Process (AHP), Binary logistic regression, Average Treatment effect (ATE).

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Introduction

Researchfindings acknowledged institutional obstacles, including hostile land tenure systems and policy conditions, and concerns relating to unsustainable agricultural practices, population growth, urban sprawl, and ineffective resource use, as hindrances to optimal maize production.Nevertheless, several of these studies paid little attention to the impact of natural variables, such as climate, terrain attributes (i.e. slope and elevation), and soil physiochemical components that give land, the chief medium of crop production its economic status(Kobe *et al.*, 2017), and its quality status to support farmers to double their production by cultivating higher-yielding IMVs(Brad *et al.*, 2020).The possibility that climate change may exacerbate erratic rainfall patterns, resulting in some locations becoming unsuitable for growing maize, has heightened food insecurity because many farmers depend on rainfall to grow crops (Akande *et al.*, 2017). Nonetheless, reports from studies conducted by Bänziger *et al.* (2006) and Tesfaye *et al.* (2018) have dispelled concerns stating that the cultivation of IMVs would mitigate the difficult impact of climate irregularities. Besides, the controversial debate surrounding the Borlaug hypothesis versus Jevons paradox regarding innovative technology adoption and land use (Rocha *et al.*, 2019) highlights the core of this research to improve the existing body of knowledge, enable impactful agricultural services that elevate farmers' productive capacity to the frontier.

Identifying a crop's essential niche is centralto its optimal growth and development and promoting the adoption of improved crop varieties (Chakraborty et al., 2021). Favourable niche conditions (including environmental and climatic factors) support improved seed variety to grow well with a resultant high yield and returns to farmers. Taking into account the foregoing, it is imperative to examine Nigeria's vast land area of 941,819 km^2, especially the 520,000 km^2that the World Bank (2016) has classified as arable, and mapping the land area per crop it best supports for optimal growth (Chukwu, 2018). The mapping exercise is pivotal because the area of land under agricultural cultivation increased from 531,765 km^2 in the early 1960s to 708,000 km2 in 2013 in Nigeria without corresponding maize supply fromthe same sector that contributes approximately 40% of the country's GDP and employs more than 65% of the national population (CIA, 2013).

Being a graminaceous C4 plant, maize (Zea mays L.) has a bundled secondary root system (at 50-70cm). The development of maize root system is favoured by the looseness of the topsoil which is warm and rich in nitrogen, phosphorous and organic matter. When these nutrients are present in sufficient proportion, they promote cation exchange capacity between the soil and maize cropsroot (Irritec, 2017), accordingly, facilitating optimal water, nutrient uptake, and solar radiation to enhance output per unit area (Nasri *et al.* 2014). Moreover, Nasri *et al.* (2014) have advocated for the practice of intercropping legumes with maize. The aforementioned practice according to Giller (2001) and Rusinamhodzi *et al.* (2012) balances the physical, chemical, and organic properties of the soil by fixing atmospheric nitrogen and consequently mitigating the probability of crop failure in the event of a drought. Maize has more economic importance than sorghum and millet thus, emphasizing its wide acceptance by people across Latin America and sub-Saharan Africa particularly among resource-poor farmers (CIMMYT and IITA, 2010). It is an affordable source of carbohydrates, vitamin B, protein, iron, and essential minerals (Adeyeye et al. 2020). In assessing the importance of maize, Umar et al (2014) reported that Nigeria through different initiatives strived to increase maize production, and as such, production peaked at 7.1 million tons in 2006. Maize production declined at a time but recovered and stabilized in 2008 through to 2010 to assume a steady positive production which cumulated at 10 million tons in 2013. In 2015, FAO reported that Nigeria ranked 14 among nations producing maize because of the 10 million tons of maize which accounted for 1.04% of the global maize produced (Aminu, 2015). In addition, this tonnage of maize according to Ezeaku et al was achieved on 4.9 million hectares of land in 2018 and projected that an additional 50 % of the same harvest has to be supplied to match the demand of the coming decades.

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Geographical Information Systems (GIS) and Remote Sensing (RS) lend themselves to reliable land suitability assessment by way of a multidisciplinary approach that aggregates factors with unique measures such as climate, land use land cover pattern, soil, terrain, and morphometric characteristics (Ande, 2011, Shalaby, 2017). According to Majumder and Saha (2018), the multicriteria decision simplifies the problem of assigning weight to criteria participating in the land suitability evaluation (Herzberg, 2019). The multi-criteria technique, for example,has been employed for the Vulnerability Assessment and Household Preparedness Level to Flood (Balogun *et al.*, 2021), Southwest Nigeria landuse land cover evaluation (NASRDA, 2017), Spatial Market Distribution of the local market (Omotoye-Omisore, 2016), Land suitability assessment for Cocoa (Kappo *et al.*, 2014), land suitability for irrigation farming (Feizizadeh and Blaschke 2013) and the citing of eco-tourism centers (Bunruamkaew and Murayama, 2011). Other multicriteria approaches available for the same purpose include outranking methods, simple additive scoring (Aldababseh *et al.*, 2018), Linear Combination, Simple limitation, fuzzy-logic modeling, Artificial Neural Networks, and the Analytical Hierarchy Process (AHP) (Orhan and Mustafa 2018; Ayla *et al.*, 2016; Alilou*et al.*, 2019; Herzberg, *et al.*, 2019). Despite the availability of other land evaluation methods, the AHP appears to be the most employed in composite decision-making of land suitability evaluation (Nguyen, 2017; Ghobadi *et al.*, 2013). AHP'sfundamental principles revolve around relating all possible criteria and determining an inclusive alternative ranking to show important criteria in the hierarchy at each level (Bozdag et al., 2016).

The result of land suitability evaluation depends on suitability grading and the purpose for which the land would be subjected. The science of integrating biophysical features with the spatial model according to FAO (2007) makes the result of land assessment reliable for policy formulation. Thus, FAO (1996) in an effort to ease the process of conducting land suitability assessment catalogued important parameters such as soil, climate, and topology of different land areas.Similarly, Herzberg *et al.* (2019) also acknowledged the scientific effort of Sys *et al.* (1993) towards gathering reference values required to plant fifty physical crops common to the tropical and sub-tropical regions of the world. While this informationassisted some land suitability evaluation processes(Abd El-Aziz, 2018, Ahmed, 2013, Shahram, 2011), others questioned the comprehensiveness and thus, found it unsuitable for their local environment.Additional information or adjustmentswere made to the document to fit their local environment (Boje*et al.*, 1998, Cools *et al.*, 2003). This underscores the importance of local information in deciding what land will be used for (Zurayk, 2001, Herzberg, 2019) and by extension illuminates the usefulness of the AHP method to this research.

Thus, this research aims to map out areas of land suitable for maize cultivation and to examine farmers'use of improved maize variety in the areas identified as suitable to grow maize in Southwest Nigeria.

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2. Methodology

This section presents the study area, data, and the theoretical framework that underpinned the application of the Geographical Information System (GIS) and Remote Sensing (RS) techniques employed to achieve the objectives of this study. In addition, the theory which guides the principle of estimating the treatment effect as it relates to farmers' use of IMV is elaborated upon in this section here.

2.1 Study area

This original research article was conducted in Owena Basin. It lies between latitude 7°43′ 0″N and 6°36′ 0″ N and latitude 4°11′ 0″ E and 4°45′ 0″ E. The area stretches from Osun state through to Ogun state covering about 3579 Km². Osun state is bounded in the north by Kwara state, to the west by Oyo state,and the East by Ekiti and Ondo states. The study area has some local governments completely in the basin (i.e. Ife Central and Ife East LG), a significant part of (Ife North and Ife South), half of (Ede South, Aiyedaade and Atakumosa West) falls in the study area while Ilesha west, Ilesha East, Ede North, Ede South, and Irewole and Isokan only have a small area in the basin. On the other hand, Ogun state is bounded by Ondo state to the East, Lagos to the South, Osun, to the North, and the Republic of Benin to the West. The study area completelyfalls in Ijebu East LG, unlike in Osun state where the study area engulfs several LGs. Osun experiences an annual average temperature of 64 °F and receives approximately 596 inches of rainfall. The annual temperature of Ogun is 84.81ºF and receives about 141.58 millimetres (5.57 inches) of rainfall annually.

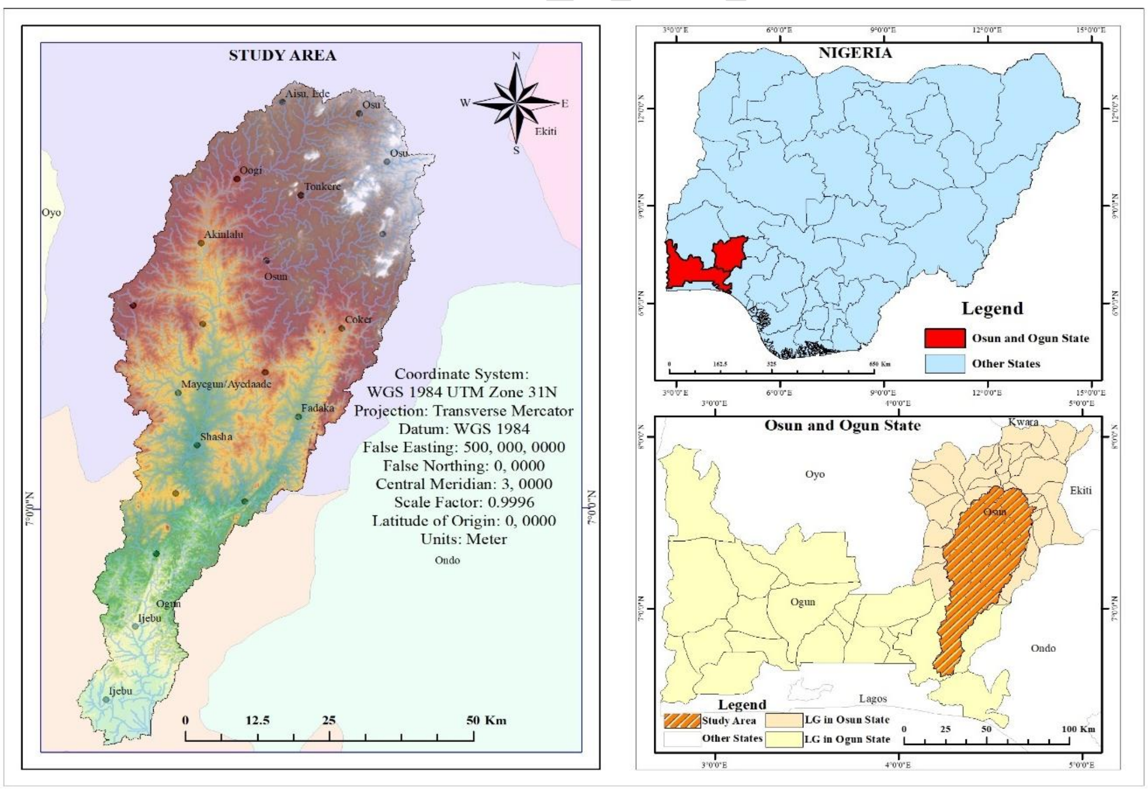

Figure 1: Map of the study

2.2. Data and methods

In this sub-section, datarequirements, soil samples, and the process of arriving at a soil fertility map are presented. Furthermore, the process of administering the questionnaire was to farmers to gather data to understand the frequency of IMV usage and the statistical model used to conduct the assessment appears here.

2.2.1 Data Requirement for Spatial Analysis

Geospatial evaluation and map results are more required as global changes impact human life. The spatial evaluation of the land suitability for maize cultivation needs criteria (presented in Table 1) upon which appropriate GIS techniques would be applied.

Table 1: Description of spatial data

Data	Source	Data type	Attribute	Extracted Data
Rainfall	Global Climatic	Secondary	30 years mean	Mean Annual
Shuttle Radar Topographic Mission (SRTM)	USGS	Secondary	30 meters	Digital Elevation Model/Slope

Source: Authors' compilation

Integration of the data features (rainfall, soil fertility, soil structure, slope, and elevation) was integrated using a multicriteria technique to map out different suitability statuses of the study area based on their support to cultivate maize. These features identified and integrated into this research work are supported by Tashayo et al. (2020), Peter et al. (2020), and Abegunde et al. (2015). Therefore, the integration of the layers using the multi-criteria assessment by inputting the raster of all the criteria as the unit for deciding the GIS variables. The data were subsequently processed using the spatial analysis tools function in the ArcMap software (ESRI, 2011). Furthermore, the process of combining the input rasters in the geospatial analysis begins with the weighted overlay analysis option in the ArcMap which allows the processing of an output raster. For each cell of the output rater, a reclassification is carried out to assign a new value. In the study, the raster out is reclassified into 4 (starting from 1). The most suitable area for maize cultivation is represented by 1 while the area least suitable takes the value of 4. The reassigned value to the reclassified raster image of the features was then weighted. The weight assigned to each feature is guided by the principle of pairwise comparison in a process called AHP. The features are ranked between 1 and 9 following Saaty's (2008) principles (See Table 2).

Table2: Description of weight assigned to criteria

Intensity	Definition	Explanation
1	Equal importance	Two elements contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favour one element over
5	Strong importance	Experience and judgment strongly favour one element over
7	Very strong importance	One element is favoured very strongly over another, its dominance is demonstrated in practice
9	Extreme importance	The evidence favouring one element over another is of the highest possible order of affirmation
2, 4, 6, and 8 can be used to express intermediate values		

Source: Klaus D. Goepel

Regarding this study, the pairwise comparison matrix of the features is in Table 3 along with the weight assigned to them. the pairwise comparison process pairs two features at a time and according to priority on one over the other as it concerns the growth of maize crop. Where the consistency ratio (CR) of the pairwise comparison of the two features is less than 10 % the matrix is considered to be consistent and

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therefore the process is continued and the same process is discontinued where the CR is greater than 10% (Park, 2011). The mathematical representation is given as follows;

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{1}$$

$$\mathrm{CR} = \frac{x-n}{n-1} \tag{2}$$

Where;

Lamda (x) is defined as the maximum Eigen value;
CI is the Consistency index CI;
CR is the Consistency Ratio;
RI is the Random Index;
N define the number of criteria or sub-criteria in each compared pairwise matrix

The pairwise comparison matrix for this study gave a CR of 6.8% which is less than the 10% required which gave a strong ground to continue to assign the weight to each of the features (Balogun et al. 2021) after which a weighted overlay was carried out to map out a land area suitable, moderately, marginally and least suitable to cultivate maize. The theory that guides the operation of AHP helps to integrate different criteria in the hierarchy of their importance (Saaty, 1977). As such, existing literature revealed that many researchers (Abdullah et al., 2020; Antwi et al.,2022; Pachemska et al., 2014) have employed AHP for different consistent land evaluation purposes. On the other hand, the literature also has many other multi-criteria methods that help assess land among which are Artificial Neural networks (Orhan et al., 2018); simple additive scoring (Aldababseh et al., 2018), ;(Alilou et al., 2019) and Linear combination and developing fuzzy-logic (Balogun et al. 2021).

Table 3: Pairwise comparison matrix

	Rainfall	Soil	Soil	Slope	Elevation	Eigen
Rainfall	1	2	2	21/4	3	33.33%
Soil fertility	1/2	1	25/6	3	3	29.23%
Soil texture	1/2	1/3	1	22/3	3	18.51%
Slope	4/9	1/3	3/8	1	24/9	11.55%
Elevation	1/3	1/3	1/3	2/5	1	7.37%

Source: Authors' computation

2.2.2 Soil sample and soil fertility map

Soil nutrients play a crucial role in the growth and development of crops. Thus, the soil sample used for this study was collected at between 0 and 25 cm depth from 12 random points on the farmlandof farmers who cultivated maize and who allowed the team to take the sample. The samples were subjected to routine laboratory procedures for analyzing soil with attention on Nitrogen (N), Phosphorous (P), Potassium (K), organic matter (Om), cation exchange capacity (CEC), and pH value based on available funds and the role these nutrient play in leaf, stem, and root of maize crop. Subsequently, the Inverse Distance Weighting (IDW) procedure was adopted to generate the raster images of the nutrients from the soil samples. The value of the nutrients following the evaluation of the soil samples show the following range of value for N (0.140002 - 0.73982 %); P (2.20233 - 3.4797 Me/100g); K (3.21703 - 42.2185 Me/100g); OM (3.14697e-006 - 9.05689 %), Cec (0.01128 - 1.5999 M/100g) and pH (high: 5.4807 - 7.21964).

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These nutrient elements were combined using the weighted sum technique. This overlayed the raster of these nutrient elements, multiplied each by an assigned weight and subsequently summing the elements together to create a soil fertility map. An important procedure in the weighted sum and use in this research is that all the multiplied inputted rasters of the nutrient elements have the same weight which equals 1. Following this procedure was the reclassification into 4 four classes highly fertile, moderately fertile, marginally fertile, and not fertile.

2.2.3 Selection technique, data gathering,and data used to examine the use of IMV

At first, the heterogeneity of the respondents posed a challenge in devising a suitable sampling technique for enumeration. However, as the spatial analysis of land suitability is a prerequisite process to the enumeration of respondents cultivating maize on suitable land, we focused on three of the four naturally revealed suitability strata: suitable, moderately suitable, and marginally suitable for maize cultivation. The fourth stratum is the non-suitable land area thus, excluded. Subsequently, we liaised with the Farmers Association of Nigeria (FAN) in each stratum and administered 750 structured questionnaires to farmers in suitable areas over four months (March to June 2021). Each stratum was allocated 250 questionnaires. A total of 466 questionnaires were returned, with 193 from the suitable stratum, 155 from the moderately suitable stratum, and 118 from the marginally suitable stratum, representing a response rate of 62 percent. The remaining questionnaires were not reckoned with because many questions in them were unanswered.

The primary data gathered from farmers to achieve the earlier stated objective include gender, access to credit, access to extension services, age of respondents, membership of farmer association of Nigeria, years in school years in farming, size of suitable farmland cultivated, household size and maize output (kg). The question asked to the farmers concerning the type of IMV they cultivated stemmed from the seed's characteristic to tolerate low rainfall and withstand disease infestation.

Chart 1. Table Description of explanatory variables

Variable	**Description and Measurement Type**	**Variable Type**
Age	Age of farmer (years)	Continuous
Gender	Gender of the farmer (1=Male; 0=Female	Categorical
Years in school	Years spent schooling (Years)	Continuous
Years in farming,	Experience in farming (Years)	Continuous
Access to credit	Have access to agricultural loan (1=Yes; 0=otherwise) (Dummy)	Categorical
Access to extension services	Have access to extension services (1=Yes; 0=otherwise) (Dummy)	Categorical
MeMAssoc	Membership of the farmer association of Nigeria(1=Yes; 0=otherwise) (Dummy)	Categorical
Size of suitable farmland cultivated	Area of land cultivated (Acre)	Continuous
Household size	Size of householding (Actual number)	Continuous
Maize output	Quantity of maize harvested (kg)	Continuous

Source: Authors' compilation

2.2.4 Statistical model to estimate the treatment effect of adoption of improved maize variety.

Technological adoption under partial population as described by Simtowe *et al.* (2016) gives theoretical support to this research. The theory's applicability draws fromthe existence of several improved maize

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developed to help farmers improve harvest under varying growing conditions. In addition, the framework avails the estimation of farmers who did not cultivateand the cultivationrate among farmers who cultivated the improved seed.

The potential outcome means (POMs), average treatment effect (ATE), and the average treatment effect on the treated (ATET) areparameters through which the effects of treatment are examined. As it concerns this article, the two potential outcomes for i^{th} farmers are y_{0i} and y_{1i}. Whereas, y_{0i} is the outcome obtainable if farmer i does not cultivate IMV, and y_{1i} if the farmer $i$cultivated IMV.

Note: y_{0i} and y_{1i} are random variables realized from y_0 and y_1.

Therefore, the distribution of the unobserved farmers–level treatment effect is stated as $y_1 - y_0$. The parameter t represents random treatment, t_i represent random treatment for i^{th} farmer, $t = 1$ is cultivationlevel, and $t = 0$ no cultivation.

Thus, the Average Treatment Effect (ATE) in the enumerated sample is stated as:

$$\text{ATE} = E(y_1 - y_0) \tag{3}$$

The mean Potential Outcome (POmean) for cultivationlevel t is:

$$\text{POM}_t = E(y_t) \tag{4}$$

The Average Treatment Effect among farmers who cultivated IMV is written as:

$$\text{ATE} = E(y_1 - y_0 | t = 1) \tag{5}$$

Where y_i is the observable outcome variable, t_i represent the treatment variable (cultivationof at least an IMV), x_i denotes the vector of covariates (i.e. access to credit, access to extension service among others) and w_i may have an element in common.

This potential-outcome model specifies that the observed outcome variables y is y_0 when $t = 0$ and that y is y_1 when $t = 1$.

Denoting this algebraically, we have:

$$y = (1 - t)y_0 + ty_1 \tag{6}$$

So that the functional forms for y_0 and y_1 will be

$$y_0 = x^{'}\beta_0 + \epsilon_0 \tag{7}$$

$$y_1 = x^{'}\beta_1 + \epsilon_1 \tag{8}$$

Where β_0 and β_1 are coefficient to be estimated, and ϵ_0 and ϵ_1 are error terms that are not related to x or w. This potential-outcome model separates each potential outcome into a predictable component, $x\beta_t$,and an unobservable error term, ϵ_t

$$t = \begin{cases} 1 \text{ if } w^{'}\gamma + \eta > 0 \\ 0 \text{ otherwise } x \end{cases}$$

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γ represents a coefficient vector, and η is an unobserved error term that is not related to either x or w. The treatment assignment process is also separated into predicated components, $w'\gamma$, and an unobservable error term, η.

The potential outcomes and the treatment are intuitively influenced by the covariates x going by the CI assumption. So, other factors that influence the treatment must not be related to the potential outcome, and any other factors that influence the potential outcome should also not be related to the treatment. Thus, the formal CI assumption states that conditional on covariates x, the treatment t is independent of the vector of potential outcomes $(y_0 y_1)'$ and this allows the estimation of the effect by regression adjustment as used in this research.

As it concerns this research the information contained in the data collected from farmers in the areas mapped as suitable to cultivate maize only discern $E(y_0|x, w, t = 0)$ and $E(y_1|x, w, t = 1)$, however, our attention is on $E(y_0|x, w)$ and $E(y_1|x, w)$, where x denotes the outcome covariates and w is the treatment assignment covariates. Thus, the CI establishes the pathway to estimate $(y_0|x, w)$ and $E(y_1|x, w)$ directly from the observation for which $E(y_0|x, w, t = 0)$ and $E(y_1|x, w, t = 1)$, respectively.

2.2.5 Statistical model to estimate factors influencing the cultivation of IMV

This section explains the relationship between the dependent variable and independent variables regardless of their attribute using a logistic regression model. The logistic model is guided by the regressand assuming a binary response of one of two values (Dipesh and Trijya, 2020; Obaid and Hassan, 2020). The value of 1 has a probability of (P) and 0 with a probability of (1-P). This then allows the logistic regression model to be stated as;

$$E(y1x) = P(y = 1) = P \tag{9}$$

Consequently, the value on the right-hand side of equation 9 will either be 1 or 0 and by applying mathematical transformation on the regressand (y) so that

$$0 \leq P \leq 1$$

We therefore have a ratio $\left(\frac{P}{1-P}\right)$ assuming a positive value between 0 and ∞.

$$0 \leq \left(\frac{P}{1-P}\right) \leq \infty \tag{10}$$

Furthermore, by taking the common logarithm in equation 10, we have:

$$-\infty \leq ln\left(\frac{P}{1-P}\right) \leq \infty \tag{11}$$

Thus, a regression model with a single regressor will be fitted as:

$$\ln\left(\frac{P}{1-P}\right) = b_0 + b_1 x_1 \tag{12}$$

Similarly, in a regression model with more than a regressor, the model is fitted as:

$$\ln\left(\frac{P}{1-P}\right) = b_0 + \sum_{i=1}^{n} b_j\, x_{ij} \tag{13}$$

$$\text{j} = 1, 2, \dots, k$$

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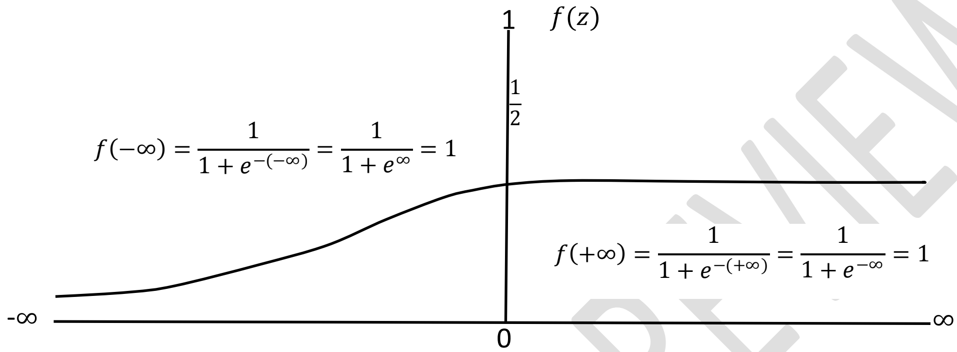
$$i = 1, 2, \ldots, n$$

Equation 13depicts the logistic regression where $\ln\left(\frac{P}{1-P}\right)$refers to the transformed logit (Obaid and Hassan, 2020). The logistic function in the graph below mirrors the logit regression model (Obaid and Hassan, 2020) where $f(z)$can bring together $-\infty, +\infty$ to 0, 1 (Dipesh and Trijya, 2020). This is essential in estimating the extent to which something or an event is likely to occur particularly when the data relating to the event is documented to take the sigmoid curve. For instance, the present study examined farmers who cultivated IMV and farmers who did not.



The choice of logistic function in regression estimation is premised on its equation range that is specified as

$$0 \leq f(z) \leq 1$$

$$P = \frac{e^{a+bx}}{1+e^{a+bx}} = \frac{1}{1+e^{-(a+bx)}}$$

rather than the straight-line equation $y = b_0 + b_1x_1 + e$.

In addition, variables to be fitted in a logit regression estimation do not have to conform with the normality assumption i.e. normally distributed. Furthermore, the regressand does not have to be linearly related to the regressor (Osbome and Jason, 2012). The logistic regression also arranges regressors in a way that eases the variable isolation and prioritization.

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Result and Discussion

Table 3 in the methodological section presents the weight assigned to each feature, indicating its degree of influence on the growth and yield of maize. The weight assignment process began with a participatory approach, where farmers were engaged to sharetheir farming experience in the process of ranking features in order of their priority. This approach gave valuable insight into determining the weight assigned to each feature. To improve the accuracy of the weight assignment process, a discussion was held with GIS and Remote Sensing experts to finalize the weight assignment for each feature. The integration of these inputs helped ensure that the weight assignment process was robust and reliable

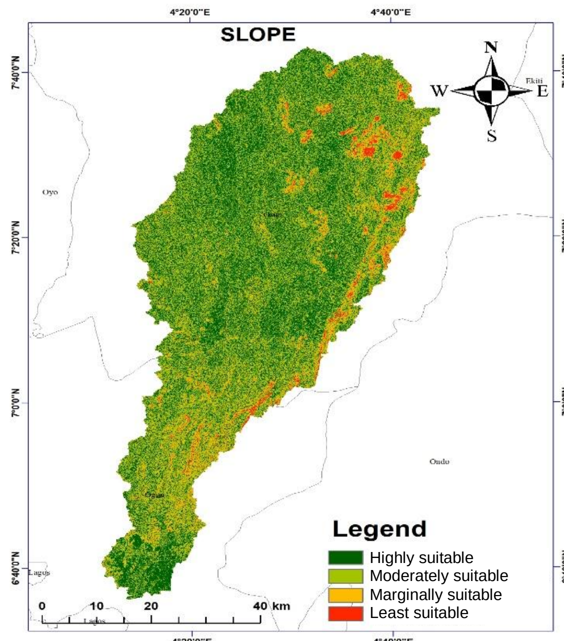


Figure 2: Slope of the study

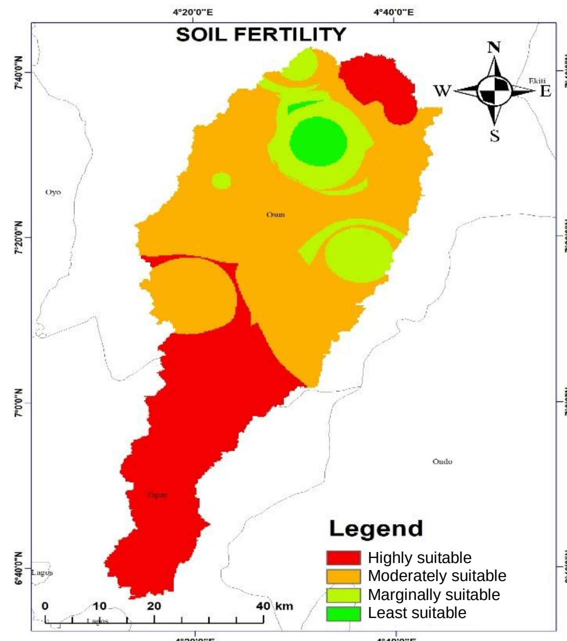


Figure 3: Soil fertility of the study

According to the findings, the feature that has the greatest impact on the success of maize production is rainfall. This outcome is supported by farmers' indication that they rely on the onset of rainfall to begin maize cultivation. As, such, rainfall was assigned 33%. Soil fertility was assigned 29 % next to rainfall as a feature required for adequate maize growth. Soil texture was assigned 19% while the slopeand elevation were assigned 12%and 7%, respectively. The weight assigned to the aforementioned features emphasizes the contribution of biophysical components to farmers' efforts to successfully cultivate maize.

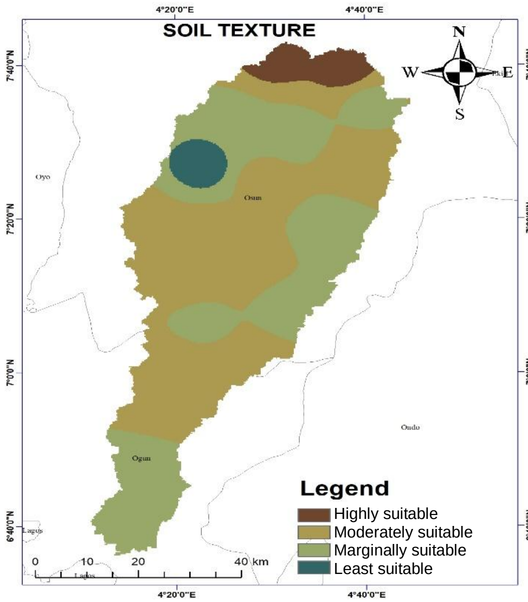


Figure 4: Soil texture of the study

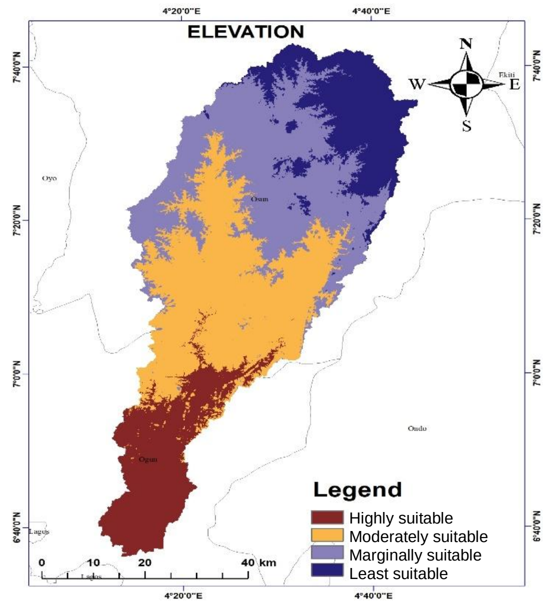


Figure 5: Elevation of the study area.

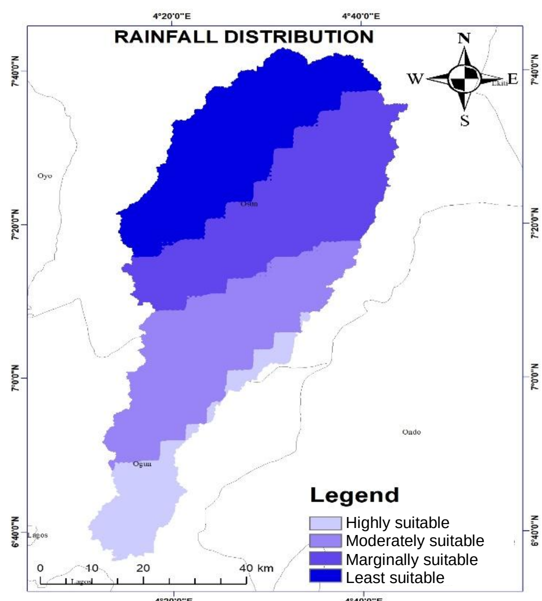
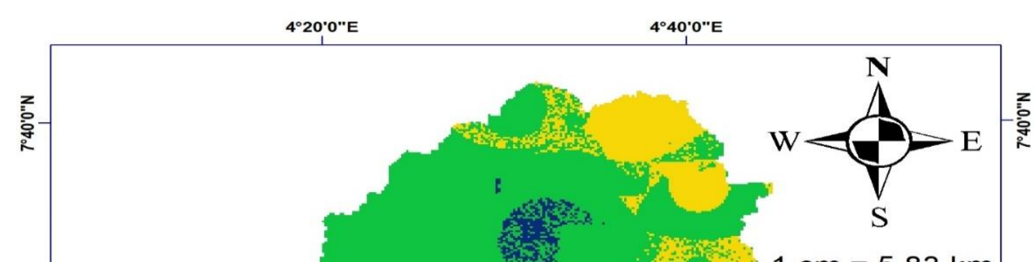


Figure 6: Rainfall distribution of the study

Therefore, the land suit[...] [...]verlaying the reclassified raster images of the featu[...] [...]gure 7. According to the map, the Highly suitable area of land spans over 180.46 km² (5.092634%). This area of land is characterized by rainfall of between 1486.75mm and 1571.84mm; loamy sand soil texture; a slope that variesbetween 0 and 3.23 degrees (0 and 5.76%) and elevation of between 0 and 117m.

The Moderately suitable area for maize cultivation is 2003.30 km², and this accounts for 56.53% of the entire study area.The rainfall distribution is observed to be between 1434.53 and 1486.75 mm. The soil texture in this area is loamy sand,with a slope of between 3.23 – 6.46 degrees (5.76-11.52%) and an elevation that varies between 117 and 206 m.



Furthermore, it was observed that 37.49% of the entire land, totalling 1328.36 km² is Marginally suitable for maize cultivation. The predominant rainfall in this area ranges from 1386.18 –1434.58mm, with a sandy loamy soil texture, a slope that ranges between 6.46 and 12.55 degrees (11.52-23.48%) and an elevation of between 206 and 290 m.

The area least suitable for maize cultivation occupies 31.39 km² and that account for 0.89% of the study area. This area is identified by rainfall that ranges from 1325.26-1386.18mm; the soil texture is sandy with a slope that ranges from 12.55-48.47 degrees (23.48-100%) and an elevation of between 290 and 685 m.

Sociodemographic description of respondents cultivating maize on suitable land

Table 4 presents a cross-tabulation of variables in whichthe age of respondents, size of land cultivated, maize output, and household size were examined under gender and years spent in school in orderto understand the characteristics of respondents that belong to the group of farmers who cultivated IMV and those that did not cultivate IMV in the study area. According to the Table, the age range of non-IMV growers varied between 50 and 61 for both males and females and across the ranges ofyears

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respondents spent schooling. On the other hand, respondents who grew IMV had their agesvarying between 52 and 72 years across gender and the ranges of years respondents spent schooling. Across the gender of respondents who have spent more than 12 years of schooling, female respondents who cultivated IMV were the eldest (72 years) while their male counterparts were the youngest (53 years) among farmers who grew IMV.

Table 4:Cross-tabulation of variables with attention on IMV growers and non-IMV growers.

Attributes of respondents		Non-Adopter	Adopters
Female respondents who have spent 0-6 years in school	Age	54	57
	Land size	2.18	2.20
	Maize output	7100	9650
	Household size	4	5
Male respondents who have spent 0-6 years in school	Age	54	56
	Land size	2.12	2.58
	Maize output	7276.22	11448.65
	Household size	4	4
Female respondents who have spent 6-12 years in school	Age	50	52
	Land size	2.15	2.84
	Maize output	7007.42	12658.82
	Household size	4.42	4.35
Male respondents who have spent 6-12 years in school	Age	52	55
	Land size	2.40	8.40
	Maize output	7666.65	12025
	Household size	4.23	4.29
Female respondents who have spent more than 12 years in school	Age	61	72
	Land size	2.23	1.9
	Maize output	8666.67	11000
	Household size	6	4
Male respondents who have spent more than 12 years in school	Age	60	53
	Land size	1.96	2.67
	Maize output	7912.5	13833.33
	Household size	5	3

Source: Authors' compilation from field survey, 2021

In addition, the resultrevealed that across the classes of years that respondentsspentschooling, the size of land cultivated varied between 1.9 and 8.40 acres of land. Furthermore, the least size of land cultivated was 1.9 acres whichwas by female respondents who cultivated IMV and schooled for more than 12 years. On the other hand, the largest area of land cultivated was observed among male respondents who cultivated IMV andcompleted between 6 to 12 years of formal education.

Among the IMV growers, the leastmaize output was recordedamong female respondents who completed between 0 to 6 years of formal education. The highest maize output recordedamong IMV growers is 13833.33kg and this was notedamong themale respondents who had completedmore than 12 years of formaleducation. Across the years spent acquiring formaleducation and gender stratification as shown in Table 4, a difference of 2550 kg was observed between the lowest maize out of farmers who cultivatedIMV and farmers who did not cultivateIMV. Similarly, a difference of 6166.66kg was observed in the highest maize output of respondents who cultivatedIMV and respondents who did not cultivate IMV.

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Across the years spent in acquiring formaleducation, gender, and grower of IMV or otherwise stratification, the household size varied between 3 and 6. Respondents who cultivated IMV were observed to have the smallest household size (3) and this household was headed by male respondents who had completed more than 12 years offormal education.

According to thefigures in Table 5, respondentswho did not cultivate IMV and were members of the farmers' association had the higher frequency across all the examined variables compared to farmers who cultivated IMV and were members of the same association.

Table5: Cross-tabulation of categorical variables under IMV growers and non-IMV growers.

Attributes of Respondents	Non-IMV Users		IMV Users	
	Membership	Non-membership	Membership	Non-membership
Respondents who are aware of improved maize variety	87	115	36	49
Respondents who had access to credit	70	79	41	36
Respondents who accessed extension services	89	107	59	59
Respondents that cultivated Local Variety	69	101	37	35
Respondents who cultivated Premier Oba Super 6	-	-	25	18
Respondents who cultivated Sweetco Hi-Brix 3 or Hi-Brix 59	-	-	29	23
Respondents who cultivated PioneerP1359 or P1185	-	-	5	6

Source: Authors' compilation from field survey, 2021

In addition, Table 5 indicated that farmers who did not cultivate IMV but were a member of the farmers' association had a better level of IMV awareness and had access to credit and extension services, compared to farmers who cultivated IMV and belonged to the same association. Surprisingly, farmers who did not cultivate IMV and are not a member of the association had a greater level of awareness of IMV, compared to farmers who cultivated IMV but were not members of the association. In addition, it was observed that farmers who cultivated IMV also grew the local maize variety, although the number was lower than those who did not cultivate IMV.

Estimation of the impact of the use of IMV among farmers cultivating maize on suitable land.

The Potential Outcome mean(POmean) in the sample of enumerated farmers is the average output of all farmers who cultivated IMV on suitable farmlandor if they did cultivate IMV. The POmean estimate of 8127.703 kg was observed as the average maize outputthat would have been harvested if the enumerated farmers had not cultivated IMV. This estimate implies that, at 95% confidence, the harvest of farmers who did not cultivate IMV will fall significantly between 6699.24 kg and 9556.113 kg. Conversely, if all the enumerated farmers cultivated IMV, the potential average maize outputthat farmers would have harvested is 11695.8 kg. From the estimation, it could be drawn that at 95% confidence, farmers who cultivated IMV would have their maize output or harvest vary significantly between 11192.91 kg and 12198.7 kg.

Table 6: The PO of respondents cultivating IMV in thearea identified as suitable for maize cultivation

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Parameters	PO means (kg)	Range of outcome	P>|Z|
Improved maize adoption rate (Probability of adopting at least one improved maize variety)			
Non-IMV Users	8127.703	6699.294 9556.113	0.000
IMV Users	11695.8	11192.91 12198.7	0.000
Probability of awareness of improved maize variety causing adoption of at least one of the improved varieties.			
Non-IMV Users	.6293833	.5504897 .708276	0.000
IMV Users	.5669662	.4519774 .681955	0.000

Source: Authors' compilation from field survey, 2021

Farmers who are aware of the existence and availability of the IMV and its potential impact on harvest are more likely to cultivate it. The results in Table 6 show that farmers' awareness level of IMV among respondents who did not cultivate IMV has a .6293833 chance of causing them to cultivate IMV. On the other hand, farmers' awareness level of IMV among farmers cultivating IMV hasa 0.5669662 chance of causing them to continue cultivating IMV or cultivate another IMV.

The ATE estimate presented in Table 7reveals that farmers who cultivated at least one IMV in areas identified as suitable harvested an average of 3568.099 kg more maize than farmers who cultivated on suitable farmland but did not cultivate IMV. The confidence interval suggests that at 95% confidence, farmers who cultivated IMV would significantly have their harvest vary between 2052.379 kg and 5083.819 kg.

Table 7: Effect of cultivating IMV in the area identified as suitablefor maize cultivation

Parameters	POmeans	Range of outcome	P>|Z|
Effect of Using IMV in the Population (ATE) (IMV users Vs Non-IMV Users)	3568.099	2052.379 5083.819	0.000
Effect of using IMV within the subpopulation that growing at least an improved maize variety (ATET).	1955.633	-2509.831 6421.097	0.391

Source: Authors' compilation from field survey, 2021

In the sub-population of farmers who cultivated at least one IMV on suitable land would on average harvest 1955.633 kg more maize compared to other farmers within the subgroup of farmers who cultivated the IMV. At a 95% confidence interval, the estimate hints that farmers who cultivate IMV on suitable farmland would have their maize output between -2509.831 kg and 6421.097 kg.

Estimation of factors influencing farmers'to cultivateIMV

The logistic regression estimation presented in Table 8reveals the factors that influence farmers to cultivate IMV on their farmland. The results indicate that the size of land under cultivation and access to extension services significantly influence farmers' likelihood to cultivate IMV.More specifically, the positive and significant coefficient of the size of land cultivated suggests that the probability of a farmer cultivating IMV on suitable land increases with the size of the land.This implies that there is at leasta 35% chance that farmers in the study area wouldcultivate IMV as the size of the land increases.

Table 8: Estimation of variables that influence farmers to cultivate IMV

Attributes	Coefficient	Std. Error	P>|z|
Gender	0.0622	.1317554	0.637
Age	0.0057	.0045463	0.251
Household size	-0.0007	.0356761	0.985
Cultivatedsize of land	0.3557	.0826285	0.000***

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Years in farming	-.0108508	.0081523	0.183
Years in school	.0158204	.0191793	0.409
Access to credit	.1445782	.1286348	0.261
Membership of Association	-.0798298	.1263515	0.528
Access to extension Service.	.5702133	.141668	0.000***
Number of respondents		465	
LR chi^2		44.23	
Prob > chi^2		0.0000	
Pseudo R^2		0.0762	

Source: Authors' compilation from field survey, 2021. (***p<0.01)

Furthermore, the results indicated that access to extension services has a positive and significant effect on the probability of a farmer cultivating IMV. Specifically, farmers with greater or uninterrupted access to extension services have 57% higher chances of cultivatingIMV.

Being a member of a farmers' association did not show a significant relationship with the cultivation of IMV, and in fact, returned a negative coefficient. Other variables, such as gender, age, years of education, and access to credit, all showed positive coefficients, although they were not significant predictors of farmers' likelihood to cultivate IMV.

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DISCUSSION

Assessing the suitability of land is crucial to sustainably maximizing profits from crop yield, especially for farmers cultivating crops like maize. To this end, researchers have conducted numerous studies to understand the phenomenon of land suitability. Notably among researchers are Alhassan *et al.* (2022), Ijeh and Amangabara (2022), Kumar *et al.* (2021), and Adeyemo *et al.* (2021) have contributed significantly in this area. Climatic information, biophysical variables, and shared experiences with local farmers about past growing seasons play a critical role in crop cultivation, particularly in regions like the study area where farmers rely on rainfall to begin planting. This underscores the importance of assessing the potential capacity of land in the Owena basin which incidentally cuts across two Southwest states, where maize is primarily cultivated without irrigation. In this regard, this study evaluated the suitability of land by mapping out areas that support optimal growth and yield of maize with attention to rainfall, soil fertility, soil texture, slope, and elevation in the assessment process. More to the point, it profiled respondents into those who cultivated IMV and those who did not, examined the potential outcome mean and identified factor(s) that influence farmers to cultivate IMV

GIS underpins the basis for assigning weights to the aforementioned biophysical parameters in order of their importance using the AHP method (Saaty, 2001; Malczewski, 2006; Thapa and Murayama, 2018). In the methodology section, this method has been explained, and the weights assigned to each parameter are clearly stated. Previous research, including, Okolie *et al.* (2019), Mulugeta *et al.* (2018) and Kumar and Jat (2017) provided useful guides in assigning weights to the parameters, and rainfall was prioritized in these studies. Consistent with this trend, this study assigned the most weight to rainfall followed by soil fertility, which aligns with farmers' experiences of critical factors for cultivating maize and assessing land suitability. Soil texture is assigned the next highest weight, followed by slope and elevation, as specified in Table 3. In the study area, soil texture is important in optimal plant germination, as finer soil textures increase the amount of nitrogen available in the soil, hold more water, and affect the release of nutrients from organic matter and their absorption by crop roots for optimal plant growth (Akiyele and Adigun, 2006 and Chukwudi *et al.*,2021).

The inclination of land, or slope, is a significant determinant of erosion and land degradation. It affects the distribution of sediment from organic carbon (C) sources and alters the process of C mineralization (Xu *et al.*, 2021), which is critical for achieving optimal crop production. Slope also affects the process of mechanization (Tashayo *et al.*, 2020) but can be beneficial when soil is transferred from higher to lower positions, creating a C-rich reservoir (Lal, 2018). However, this beneficial effect can counterbalance the loss of gases of other larger nutrient components in the greenhouse gas balance (Henault *et al.*, 2012).

The elevation or altitude of the land plays a crucial role in exposing crops to environmental factors, including temperature, precipitation, and sunlight. As such, it has a significant influence on crop growth and development (Dalerum *et al.*, 2019). A high or low elevation determines the intensity of sunlight that drives the photosynthetic process, which fuels optimal crop growth and eventual yield (Özden, 2020).

According to the study, farmers who did not cultivate IMV tended to be older, with an age varying between60and61 years for both genders. This suggests that respondents may be less likely to adopt new farming practices, including the use of IMV. This is because older farmers tend to be more conservative aboutfarming customs and practices they used to over the years. This position aligns with the observation of Udimal *et al.* (2017) documented in their article where older farmers were reluctant to invest in agricultural technology in the Northern Region of Ghana. Therefore, it is important to improve the robustness of extension services to help this group of farmers understand the benefits of cultivating IMV. In addition, the regular presence of extension services may likely attract new and younger farmers to cultivate IMV in the study area. Supporting the need for this suggestion is Mausch *et al.* (2019) who reported a positive relationship between access to extension services and the use of improved seed varieties among farmers in Kenya.

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The study also found that farmers who cultivated IMV were mostlysmall-scale farmers. Given that a large expanse of land (classified as highly, moderately and marginally) has been identified as suitable for maize cultivation illuminate the opportunity available to farmers in the study area to scale up their production by expanding the area of land under cultivation. While this result hintsata system which makes farmers' access to land difficult, it also emphasizes the need to dismantle whatever bottlenecks hindering farmers' access to cultivate more land in the study area. The foregoing submission is important given that Gebrehiwot *et al.* (2020) and De Groote *et al.* (2019), reported a positive relationship between the use of improved varieties and farmers with larger land holdings. Although Tambo and Wünscher (2021) reported a positive link between the use of improved maize varieties and food security among small-scale farmers, they could not establish a positive relationship with the size of the farmland cultivated. Overall, the study aligns with the notion that farmers with larger land holdings are more likely to cultivate IMV.

Interestingly, the study found that farmers who did not cultivate IMV had greater access to credit than those who did. This finding agreed with the report of Lemecha (2023) who observed that farmers who did not adopt agricultural technologies, such as improved seeds and fertilizers, had greater access to agricultural loans than farmers who did adopt these technologies in Ethiopia. This hints at a possibly inefficient loan disbursement system that requires repositioning, and thorough screening of the farmers' applications to ensure credit reaches farmers who demonstrate competence in input/resource allocation.This will enhance the process of scaling food production and achieving food self-sufficiency.

Contrary to expectations, being a member of a farmers' association did not show a significant relationship with the cultivation of IMV and in fact, it returned a negative coefficient. This finding is surprising, as a general notion might lean towards believing that being a member of such an association provides a platform for exchanging ideas and knowledge, which could improve farmers' exposure to new farming practices such as the use of IMV. This result contradicts the findings of Abay *et al.* (2021) and Mengistie and Gebreegziabher (2020), who reported a positive influence of association membership on the quality of farm decision-making by farmers.

The ATE estimate indicates that farmers who cultivated IMV had a significantly higher harvest compared to those who did not within the entire sample. Meanwhile, the ATET estimate, although smaller than the ATE estimate, shows that farmers who grew IMV within a subpopulation experienced varying levels of harvest. However, the lower boundary of the ATET confidence interval estimate includes zero or negative values, which suggests that the treatment did not increase the harvest of some farmers. This hintsthat some farmers were unable to optimally allocate their input resources, causing a negative impact on their harvest. This finding contradicts those of Asfaw and Lipper (2011) and highlights the need for additional information on the technical efficiency of farmers who cultivated IMV and farmers who did not in order to understandthe scheme of events in the study area during theirfarming season. Notably, the ATE and ATET estimate is less than the mean potential outcome suggesting that some farmers may not have realized the full benefits of IMV cultivation.

Conclusion andRecommendation

First, this study applied the GIS and MCA techniques to map out suitable land for maize cultivation in Nigeria's Owena basin. Besides, it employed cross-tabulation to profile farmers into those who cultivate IMV and those who did not cultivate IMV, used the treatment effect approach to examine potential outcomes between and within the classes of farmers initially profiled, and examined factors that cause farmers to cultivate IMV in the study area.

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The GIS and MCA were useful techniques and successfully identified (highly, moderately, and marginally) land that farmers can use to increase their yield by expanding their acreage of cultivation. Furthermore, the study divulged that farmers in the study area are old with the majority cultivating on a small scale with a maize yield that could be scaled up. The respondents' household was averagely observed to be small. These observations manifest across both classes of farmers (i.e. those who cultivate IMV and farmers who did not cultivate IMV). The farmers who did not cultivate IMV were more in number, had a higher awareness level of IMV, and had access to credit and extension services compared to farmers who cultivated IMV in the study area. The study also showed that farmers who cultivated IMV also cultivated the local maize variety.

The Potential outcome mean estimation on the general sample showed that IMV yielded higher output compared to the output of farmers who did not cultivate IMV. However, the effect of cultivating IMV within the sub-population of farmers who cultivated IMV was lower when compared to the mean potential output. In fact, in other instances, the output was not different to zero which hints at a gap in the allocation of resources or the use of other resources during the cultivation season which other farmers did not use.

The size of the suitable land cultivated and farmers' access to extension services were observed to significantly cause farmers in the study area to cultivate IMV and also keep farmers already cultivating IMV to continue cultivating it or cultivate another IMV.

This study therefore recommends that the current extent of land suitability profiling be expanded so that land would be used optimally and sustainably by cultivating the crop that an area best supports for optimal growth, development, and yield. Furthermore, a study on resource use efficiency should be conducted to give more understanding as to why IMV did not generate positive output within the sample of farmers that cultivated IMV in the study area. It is important that radical extension services engagement and support are readily available to farmers on how best to use innovative technology like IMV. More importantly, the outcome of this research should be shared and communicated with the extension officer, farmers, and other stakeholders in the study area to aid their understanding of the capacity of their farmland to cultivate a particular crop. Doing this may spur the use of necessary management practices to increase productivity and by extension maize yield while ensuring sustainable land use.

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Reference

Abay, K. A., Berhane, G., Taffesse, A. S., and Koru, B. (2021). The Effect of Farmers' AssociationMembership on Agricultural Technology Adoption and Household Welfare: Evidence from Ethiopia. Journal of African Economies, 30(1), 68-94. doi: 10.1093/jae/ejaa028

Abd El-Aziz, S.H. (2018). Evaluation of land suitability for main irrigated crops in the North-Western Region of Libya. Eurasian J. Soil Sci. 7, 73–86.

Abdullah, N., Zolkafli, A., Mansor, N. S. and ChiK, N. A. (2020). Farmer's Knowledge in Land Suitability Evaluation and Farmers' Awareness in Organic Farming for Sustainable Agriculture: A Case Study in Perlis. IOP Conf. Series: Earth and Environmental Science 616, 012041 doi:10.1088/1755-1315/616/1/012041

Abegunde, L., Adedeji, O., and Tope-Ajayi, O. (2015).Land Suitability Analysis for Maize Production in Egbeda Local Government Area of Oyo State Using GIS Techniques. World Academy of Science, Engineering and Technology International Journal of Environmental and Ecological Engineering Vol:9, No:3.

Adeyemo, A. J., Akintoye, H. A., and Arowosegbe, O. O. (2021). Land suitability evaluation for maize and cassava farming using GIS and remote sensing techniques: a case study of Akure South Local Government Area, Ondo State, Nigeria. African Journal of Agricultural Research, 16(7), 1168-1180.

Adeyeye, A.O., Olaoye, S. O and Adeyanju, A. O. (2020). Evaluation of nutrient composition and functional properties of maize flour blends fortified with cowpea flour. Cogent Food & Agriculture, 6(1), 1729118. doi: 10.1080/23311932.2020.1729118

Ahmed, S. (2013). Evaluation of the land resources for agricultural development. Case study: El-Hammam Canal and Its Extension, NW Coast of Egypt. Ph.D. Thesis, University of Hamburg, Hamburg, Germany.

Akande, A., Costa, A. C., Mateu, J. and Henriques, R. (2017). Geospatial analysis of extreme weather events in Nigeria (1985–2015) using self-organizing maps. *Adv. Meteorol.***2017**, 8576150. https://doi.org/10.1155/2017/8576150

Akinyele, B. O. and Adigun, A. B. (2006). Soil Texture and the Phenotypic Expression of Maize (*Zea mays* L.). *Research Journal of Botany, 1: 139-143*.**URL:**https://scialert.net/abstract/?doi=rjb.2006.139.143

Al Zawbaee, O. M. M. and Tabra, H. M. (2020). Identifying factors influencing decision making using logistic regression. Available online at www.refaad.com Gen. Lett. Math., 8(2) (2020), 83- 89 Research Article.

Aldababseh A, Temimi M, Maghelal P, Branch O, Wulfmeyer V. (2018). "Multi-Criteria Evaluation of Irrigated Agriculture Suitability to Achieve Food Security in an Arid Environment" Sustainability. ;10:803.

Aldababseh, A., Temimi, M., Maghelal, P., Branch, O. and Wulfmeyer, V. (2018).Multi-Criteria Evaluation of Irrigated Agriculture Suitability to Achieve Food Security in an Arid Environment.

Alhassan, A., Ahmad, N., and Ismail, M. A. (2022). Assessment of land suitability for rice cultivation using GIS and AHP: A case study of the Kano River Irrigation Project, Nigeria. Geocarto International, 37(1), 79-93.

UNDER PEER REVIEW

Alilou H, Rahmati O, Singh VP, Choubin B, Pradhan B, Keesstra S, (2019). "Evaluation of watershed health using Fuzzy-ANP approach considering geo-environmental and topo-hydrological criteria," J. Environ. Manag.232:22–36.

Alilou, H., Rahmati, O., Singh,V.P., Choubin, B., Pradhan, B., Keesstra, S., Ghiasi, S.S. and Sadeghi, S.H (2019). Evaluationof watershed health using Fuzzy-ANP approach considering geo-environmental and topo-hydrologicalcriteria. J. Environ. Manag., 232,22–36.

Ande, O. T. (2011). Soil Suitability Evaluation and Management for Cassava Production in the Derived Savanna Area of Southwestern Nigeria.

Antwi, E. K., Setiawati, M. D., Tetteh, J. D., Boakye-Danquah, J., Owusu-Banahene, W. and Yohuno, (Aponti) P. T (2022) . Agricultural Land Suitability Assessment towards Promoting Community Crop Production in Tolon-Ghana. DOI: https://doi.org/10.21203/rs.3.rs-1733563/v1

Asfaw, S., and Lipper, L. (2011). Adoption of improved maize varieties and farmers' welfare in Ethiopia. International Food Policy Research Institute (IFPRI) Discussion Paper 01084.

Ayla, B., Fadim, Y. and Aslı, D. (2016). AHP and GIS-based land suitability analysis for Cihanbeyli (Turkey) County.Environ. Earth Sci. 75, 813–823.

Balogun, T. A., Adamu, M. O., Alaga, T., Adewoyin, J. E., Ajisafe, S. A. and Nuhu, S. (2021). Vulnerability Assessment and Household Preparedness Level to Flood in Ogunpa-Oni Sub River Basin. *Asian Journal of Environment & Ecology 16(4): 17-31,Article no.AJEE.74172, ISSN: 2456-690X.*

Bänziger, M., Setimela, P. S., Hodson, D. and Vivek, B. (2006). Breeding for improved abiotic stress tolerance in maize adapted to southern Africa. *Agric. Water Manag.***80**, 212–224.

Boje, G.; Rücker, G.; Senzige, S.; Skowronek, A. Skowronek. (1998). Land Suitability for Crop Diversification and Yield Potential of Drained Swamp Area in NW-Tanzania. Tropenlandwirt-J. Agric. Trop. Subtrop. 99 65–75.

Bozdag, A., Yavuz, F. and Günay, A.S. (2016). AHP and GIS-based land suitability analysis for Cihanbeyli (Turkey) county. Environ. Earth Sci. 75, 813.

Bunruamkaew, K. andMurayam, Y. (2011). Site suitability evaluation for ecotourism using GIS and AHP: A case study ofSurat Thani province, Thailand. Procedia Soc. Behav. Sci.21, 269–278.

Chakraborty, U., Chakraborty, B., and Datta, A. (2021). Crop niche development for sustainable agriculture. Current Opinion in Environmental Science and Health, 20, 100238.

Chukwu, E. O. (2018). Economic Analysis of Aggregate Agricultural Land Resources Quality in Nigeria. European Journal of Agriculture and Forestry Research Vol6, No.2, pp.1-15.

Chukwudi, U. P., Kutu, F. R. and Mavengahama, S. (2021). Influence of Heat Stress, Variation in Soil Type, and Soil Amendment on the Growth of Three Drought Tolerant Maize Varieties. Agronomy, Vol. 11, Issue 8, 1485.

Cools, N., De Pauw, E. and Deckers, J. (2003). Towards an integration of conventional land evaluation methods and farmers' soil suitability assessment: A case study in northwestern Syria. Agric. Ecosyst. Environ. 95, 327–342.

UNDER PEER REVIEW

Dalerum, F. , Retief, T. , Havemann, C. P. , Chimimba, C. T. , and Van Rensburg, B. J. (2019). The influence of distance to perrenial surface water on ant diversity in Mopane Woodlands, northern Botswana. Ecology and Evolution, 9, 154–165. 10.1002/ece3.4692

De Groote, H., Ajeigbe, H. A., Vanlauwe, B., and Kanampiu, F. (2019). The effects of adoption of improved maize varieties on farm households' welfare in Nigeria. Food Policy, 87, 101740. doi:10.1016/j.foodpol.2019.101740

ESRI, (2011) "Spatial Analysis and Data Science; Available:https://www.esri.com/en-us/arcgis/products/spatial-analytics-data-science/capabilities/visualization-exploration.

Ezeaku, I. E., Okechukwu, E. C. and Aba, C. (2014). Climate change effects on maize production in Nigeria and strategies for mitigation. *Asian J. Sci. Technol.***5**, 862–871.

FAOSTAT. Food and Agriculture Organization of the United Nations. http://faostat.fao.org. (2018).

Feizizadeh, B. and Blaschke, T. (2013). Land suitability analysis for Tabriz county, Iran: A multi-criteria evaluationapproach using GIS. J. Environ. Plan. Manag. 56, 1–23.

Food and Agriculture Organization of the United Nations. Land Evaluation (2007). Towards a Revised Framework; FAO: Rome, Italy.

Gebrehiwot, T., D'Haese, M., Deckers, J., and Nyssen, J. (2020). Does adopting improved chickpea variety improve smallholder farmers' income? Evidence from Ethiopia. Agricultural Economics, 51(1), 87-97. doi:10.1111/agec.12559

Ghobadi, M.,Babazadeh, R., Bagheri, V. (2013). Siting MSW landfills by combining AHP with GIS in Hamedanprovince, western Iran. Environ. Earth Sci. 70, 1823–1840.

Henault, C., Grossel, A., Mary, B., Roussel, M., Leonard, J. (2012). Nitrous oxide emission by agricultural soils: A review of spatial and temporal variability for mitigation. Pedosphere 22, 426–433.

Herzberg, R., Pham, T. G., Kappas, M., Wyss, D. and Tran, C. (2019).Multi-Criteria Decision Analysis for the Land Evaluation of Potential Agricultural Land Use Types in a Hilly Area of Central Vietnam.

Ijeh, I. I., and Amangabara, G. T. (2022). GIS-based land suitability analysis for maize (Zea mays L.) cultivation in Isuikwuato Local Government Area of Abia State, Nigeria. Applied Ecology and Environmental Research, 20(1), 295-311.

Kappo, A., Rilwan, M. L. and Muibi, K. (2014). Land Suitability Assessment for Cocoa Cultivation in Ife Central Local Government Area, Osun State.

Karki, D. and Kafle, T. (2020) Investigation of Factors Influencing Risk Tolerance among Investors using Ordinal Logistic Regression: A case from Nepal., Cogent Economics & Finance, 8:1, 1849970, DOI:10.1080/23322039.2020.1849970

Kim, I., and Mohammed, I. (2013). The effects of land tenure practices on agricultural output in AgatuLocal Government Area of Benue State, Nigeria. Journal of Development and Agricultural Economics, 6(5), 212–219. DOI: 10.5897/JDAE12.158 Article Number: E722CB344315 ISSN 2006-9774.Retrieved from http://www.academicjournals.org/journal/JDAE/article-full-text-pdf/E722CB344315

UNDER PEER REVIEW

Kobe, I.H. Olamide, O. E., Bamidele, F. S., Benedict,A.T., Yemisi, B. K. and Kamal, D. A. (2017). Economic Assessment of Agricultural Land Market in Rural Nigeria: Pattern and Drivers. Journal of Land and Rural studies 6(1) 50-66 Sage Publication. DOI: 10.1177/2321024917732889.

Kumar, S., and Jat, M. L. (2017). Land suitability analysis for rainfed agriculture using remote sensing and GIS techniques. Journal of Environmental Management, 193, 366-376. https://doi.org/10.1016/j.jenvman.2017.02.014

Kumar, V., Kumar, P., Pandey, A., Singh, A. K., and Singh, S. K. (2021). Land suitability analysis for maize crop using GIS and AHP techniques: A case study of Kaimur plateau region, India. Geocarto International, 1-22.

Lal, R. (2018). Digging deeper: A holistic perspective of factors affecting soil organic carbon sequestration in agroecosystems. Glob. Change Biol. 24, 3285–3301.

Lasun, M. O. (2006). Land reform-experience from Nigeria: Promoting land administration and good governance:5th FIG Regional Conference. Accra, Ghana. Retrieved from https://www.fig.net/resources/proceedings/fig_proceedings/accra/papers/ts18/ts18_02_olayiwola_adeleye.pdf

Lemecha, M. E. (2023). Credit access and agricultural technology adoption in Ethiopia: evidence from a household survey. Agricultural Finance Review, 83(3), 395-415.

Majumder, M and Saha, A. K (2018). Feasibility Model of Solar Energy Plants by ANN and MCDM Techniques.

Malczewski, J. (2006). "GIS-based multicriteria decision analysis: a survey of the literature." International Journal of Geographical Information Science, 20(7), 703-726.

Malczewski, J. (2006). GIS-based multicriteria decision analysis: A survey of the literature. Int. J. Geogr. Inf. Syst.20, 703–726.

Mausch, K., Fongar, A., and Bello-Bravo, J. (2019). The impact of agricultural extension on technology adoption: evidence from a randomized control trial in Kenya. Agricultural Economics, 50(2), 139-153. doi:10.1111/agec.12472

Mengistie, B. T., and Gebreegziabher, Z. (2020). The Impact of Farmer Group Membership on Smallholder Farmers' Technical Efficiency: Empirical Evidence from Ethiopia. Journal of Agricultural and Applied Economics, 52(1), 60-82. doi: 10.1017/aae.2019.35

Mikhailovich, B. A. (2011). Artificial Breeding in Pisciculture, and Breeding of Rare and Endangered Species of Freshwater Fish.

Mulugeta, M. T., Asfaw, Z., and Senay, G. B. (2018). Land suitability analysis for crop production using multi-criteria decision analysis (MCDA) and GIS in the Tekeze River Basin, Ethiopia. Agriculture, 8(7), 95. https://doi.org/10.3390/agriculture8070095

Nguyen, H.H. (2017). Evaluation of Coastal Sandy Land in Thanh Hoa province for Agricultural Development withCase study of Quang Xuong district. Ph.D. Thesis, Faculty of Mathematics and Natural Sciences, Greifswald,Germany.

UNDER PEER REVIEW

Odetola, T. and Etumnu, C. (2013) Contribution of Agriculture to Economic Growth in Nigeria, the 18th Annual Conference of the African Econometric Society (AES Accra, Ghana at the session organized by the Association for the Advancement of African Women Economist (AAAWE), 22nd and 23rd July, 2013).

Okolie, C. L., Eze, C. C., and Nwachukwu, M. A. (2019). Assessment of land suitability for crop production using GIS and remote sensing techniques in Uzo-Uwani LGA, Enugu State, Nigeria. Journal of Environmental Geography, 12(1-2), 35-46. https://doi.org/10.2478/jengeo-2019-0003

Omotoye-Omisore, O., Samson, S. A., Alaga, A. T.,Ogbole, J., Ogunyemi, S. A. and oloko-Oba, M. O. (2016). Spatial Distribution ofLocal Marketsin Ife North Local Government Area. International Journal of scientific and Technology Research vol. 5 (8). ISSN 2277-86165IJSTR.

Orhan D, Mustafa U. (2018). Multi-criteria approach with linear combination technique and analytical hierarchy process in land evaluation studies," Eurasian J. Soil Sci. 7:20–29.

Orhan, D.and Mustafa, U.(2018). Multi-criteria approach with linear combination technique and analytical hierarchyprocess in land evaluation studies. Eurasian J. Soil Sci., 7, 20–29.

Osbome, W. and Jason (2012). Logits and tigers and bears, oh my! A brief look at the simple math logistic regression and how it can improve dissemination of results. Practical Assessment, Research and Evaluation,17(11) (2012),1-10.

Özden, Dr Seray. (2020). The Effect Of Altitude On The Growth And Development Of Trojan Fir (Abies nordmanniana subsp. equi-trojani [Asch. and Sint. ex Boiss] Coode and Cullen) SAPLINGS. CERNE. 26.392. 10.1590/01047760202026032 73

Pachemska, T. A., Lapevski, M. and Timovski, R. (2014). Analytical Hierarchical Process (Ahp) Method Application In The Process Of Selection And Evaluation. *International Scientific Conference"UNITECH 2014" – Gabrovo.*

Park S. (2011). Prediction and comparison of urban growth by Land Suitability Index Mapping using GIS and RS in South Korea," Landscape and Urban Planning, 99:104-114.

Peter, B. G., Messina, J. P., Lin, Z. and Snapp, S. S. (2020). Crop climate suitability mapping on the cloud: a geo-visualization application for sustainable agriculture. Scientific Reports10:15487 Available at: https://doi.org/10.1038/s41598-020-72384-x

Rocha, A., Gonçalves, E., Almeida, E. (2019). Agricultural technology adoption and land use: evidence for Brazilian municipalities. Journal of Land Use Science, vol.14, Nos.4-6, 320-346. Available athttps://doi.org/10.1080/1747423X.2019.1707312

Saaty T. (1977) "A scaling method for priorities in hierarchical structures," Journal of Mathematical Psychology, Vol15:234-281.

Saaty, T. L. (2001). "Decision making with dependence and feedback: The Analytic Network Process." RWS Publications.

Saaty, T. L. (2008). Decision-making with the analytic hierarchy process. Int. J. Service Sci. 1, 83-98.

UNDER PEER REVIEW

Shahram, A. (2011). Land suitability evaluation for irrigated barley in Damghan Plain, Iran. Indian J. Sci. Technol. 4, 1182–1187.

Shalaby, A.; AbdelRahman, M.A.E.; Belal, A.A. (2017). A GIS-Based Model for Land Evaluation Mapping: A CaseStudy North Delta Egypt. Egyptian J. Soil Sci. 57, 339–351.

Smit, B., and Skinner, M. W. (2002). Adaptation options in agriculture to climate change: A typology. Mitigation and Adaptation Strategies for Global Change, 7(1), 85-114. doi: 10.1023/A:1015862228270

Tadesse, T., and Shimeles, A. (2019). Climatic Variability and Its Impacts on Farming in Ethiopia: Panel Evidence from Household Farming Systems. Sustainability, 11(8), 2366. doi: 10.3390/su11082366

Takeshima, H. and Adesugba, M. A. (2015). Irrigation Potential in Nigeria: Some Perspective Based on Factor Endowmwents, Tropical Nature, and Patterns in Favourable Areas.

Tambo, J. A., and Wünscher, T. (2021). The impact of improved maize varieties on food security: Evidence from smallholder farmers in Ethiopia. Food Security, 13(3), 619-633. doi:10.1007/s12571-021-01157-6

Tashayo, B., Honarbakhsh, A., Akbari, M. and Eftekhari, M (2020). Land suitability assessment for maize farming using a GIS-AHP method for a semi-arid region, Iran. *Journal of the Saudi Society of Agricultural Sciences*.DOI: https://doi.org/10.1016/j.jssas.2020.03.003

Tesfaye, K., Kruseman, G., Cairns, J. E., Zaman-Allah, M., Wegary, D., Zaidi, P. H., Boote, K. J. Rahut, D. and Erenstein, O. (2018). Potential benefits of drought and heat tolerance for adapting maize to climate change in tropical environments,Climate Risk Management,Volume 19, pp106-119,ISSN 2212-0963,https://doi.org/10.1016/j.crm.2017.10.001

Thapa, R. B., and Murayama, Y. (2018). "Land-use suitability analysis using GIS-based multicriteria decision-making approach and AHP model in Kathmandu Metropolitan City, Nepal." Geomatics, Natural Hazards and Risk, 9(1), 191-207.

Udimal, T. B., Jincai, Z., Mensah, O. S. and Caesar, A. E. (2017). Factors Influencing the Agricultural Technology Adoption: The Case of Improved Rice Varieties (Nerica) in the Northern Region, Ghana, Journal of Economics and Sustainable Development www.iiste.org ISSN 2222-1700 (Paper) ISSN 2222-2855 (Online) Vol.8, No.8.

Ukaejiofo, A. N. (2009). Identifying appropriate tools for land governance in Nigeria. Spatial data serving people: Land governance and the environment-building the capacity. Hanoi, Vietnam. Retrieved from https://www.fig.net/resources/proceedings/fig_proceedings/vietnam/papers/ts01b/ts01b_ukaejiofo_3643.pdf
World Bank (2016). Data report on agricultural land. Retrieved from http://data.worldbank.org/indicator/AG.LND.AGRI.K2

World Bank. 2014. *World Development Indicators*. Washington, DC.; Falkenmark, M. 1989. "The Massive Water Scarcity Threatening Africa—Why Isn't It Being Addressed." *Ambio*18 (2): 112–118.

World Economic Forum (2017). Shaping the future of Global Food Systems: A Scenarios Analysis.

Xu, M., Cardenas, L. M., Horrocks, C. A., Lopez-Aizpun, M., Zhang, J.,Zhang, F. and Dungait, J. A. J. (2021).

UNDER PEER REVIEW

The effect of tillage management on microbial functions in a maize crop at different slope positions. *Geoderma*. 401, p. 115171. https://doi.org/10.1016/j.geoderma.2021.115171

Zurayk, R.; el-Awar, F.; Hamadeh, S.; Talhouk, S.; Sayegh, C.; Chehab, A.-G.; Shab, K.A. (2001) Using indigenous knowledge in land use investigations: A participatory study in a semi-arid mountainous region of Lebanon. Agric. Ecosyst. Environ. 86, 247–262.

UNDER PEER REVIEW