Land Suitability Evaluation: A Key to Sustainable Crop Production in the 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: Suitability evaluation, Analytic Hierarchy Process (AHP), Binary logistic regression, Average Treatment effect (ATE), Improved Maize Variety (IMV).

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 in order 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.

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.

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 Km^2. 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 AtakumosaWest) 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 LG. 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.

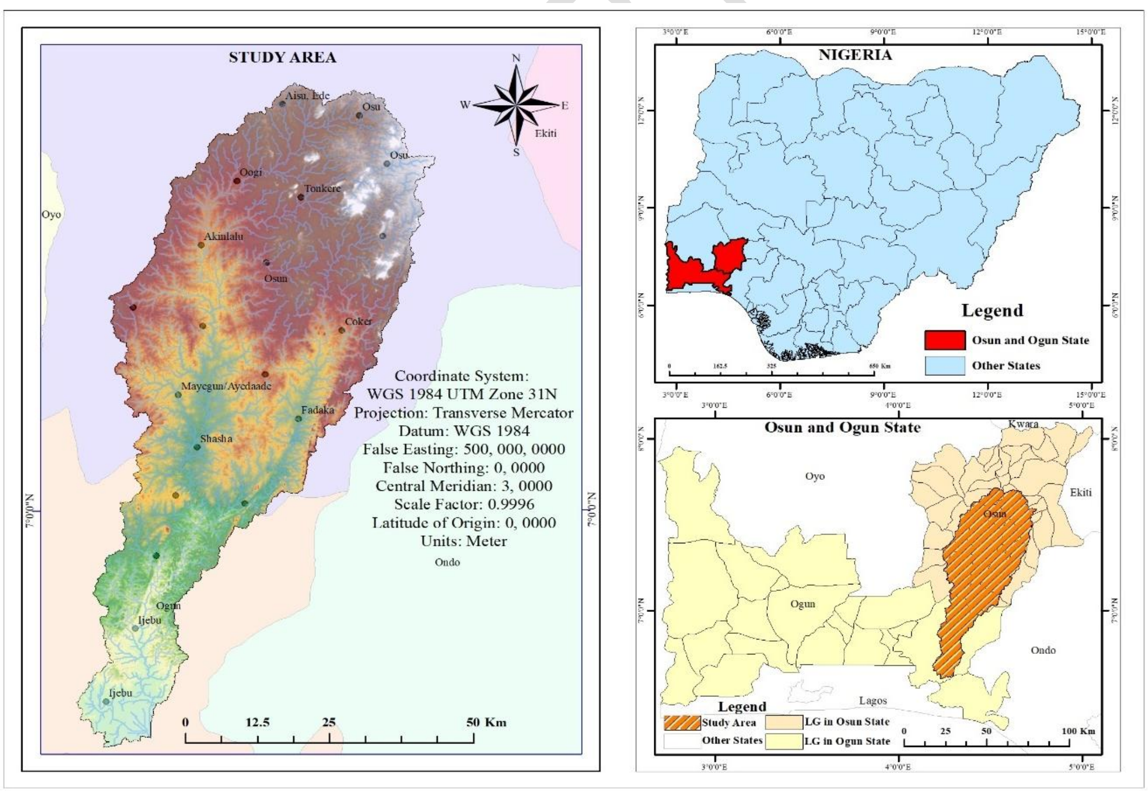


Figure 1: Map of the study

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

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 favourone element over
5	Strong importance	Experience and judgment strongly favourone 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 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;

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

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

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).

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 resides in the belief and the existence of several improved maize developed to help farmers improve harvest under varying growing conditions. However, the reality is that only a few farmers have taken advantage of the varieties by cultivating them. In addition, the framework avails the estimation of farmers who did not adopt and the adoption rate among farmers who adopted the technology.

The potential-outcome means (POMs), average treatment effect (ATE), and the average treatment effect on the treated (ATET) parameters through which treatment effects are estimated. As it concerns this research, the two potential outcomes for i^{th} farmers are y_{0i} and y_{1i}. Whereas, y_{0i} is the outcome that would be obtained if farmer i does not adopt improved maize variety, and y_{1i} if farmer i adopts the improved variety.

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 by i^{th} farmer, $t = 1$ is adoption level, and $t = 0$ no adoption level.

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

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

The mean Potential Outcome (POmean) for adoption level t is:

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

And the Average Treatment Effect among farmers that adopted the improved maize variety:

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

Where y_i is the observable outcome variable, t_i represent the treatment variable (adoption of at least an improved maize variety), 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:

$$y = (1 - t)y_0 + ty_1$$

So that the functional forms for y_0 and y_1 will be

$$y_0 = x' \beta_0 + \epsilon_0$$

$$y_1 = x' \beta_1 + \epsilon_1$$

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

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

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 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, and 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;

$$E(y1x) = P(y = 1) = P$$

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

$$0 \leq P \leq 1$$

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

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

Furthermore, by taking the common logarithm, we are able to derive

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

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

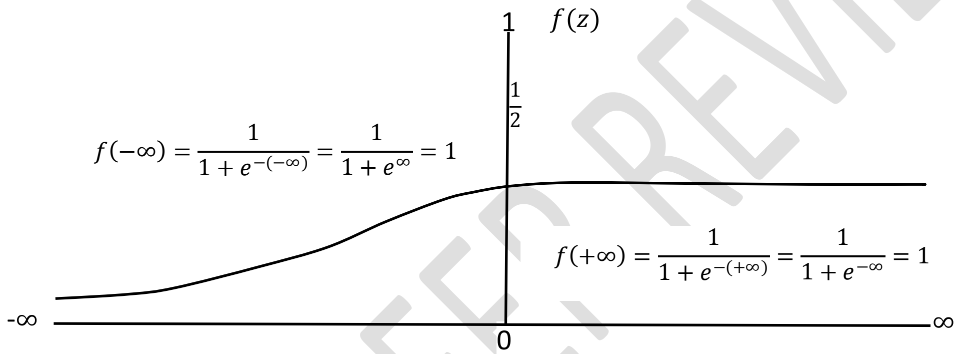
$$\ln\left(\frac{P}{1-P}\right) = b_0 + b_1 x_1$$

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

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

$$\text{j} = 1, 2, \ldots, k$$
$$\text{i} = 1, 2, \ldots, n$$

The equation above depicts 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 $f(z)$ has the capacity to 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 particular when data relating to the event documented to take the sigmoid curve. For instance, and as it relates to the present study where the farmers are examined farmers who cultivate IMV and those that 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.

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 based on their 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

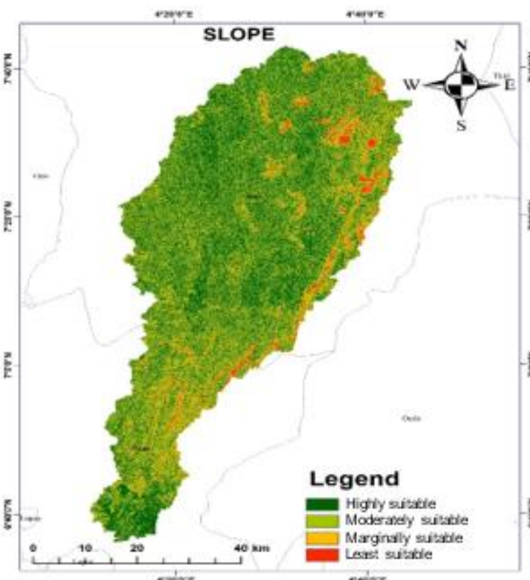


Figure 2: Slope of the study area.

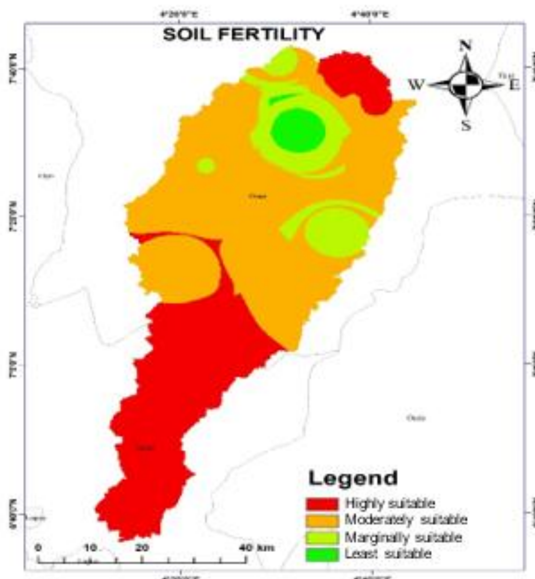


Figure 3: Soil fertility of the study area.

According to the findings of the study, 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 slope and 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.

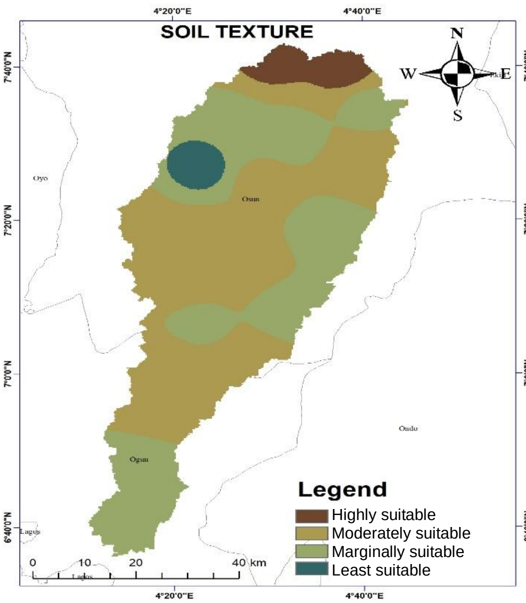


Figure 4: Soil texture of the study

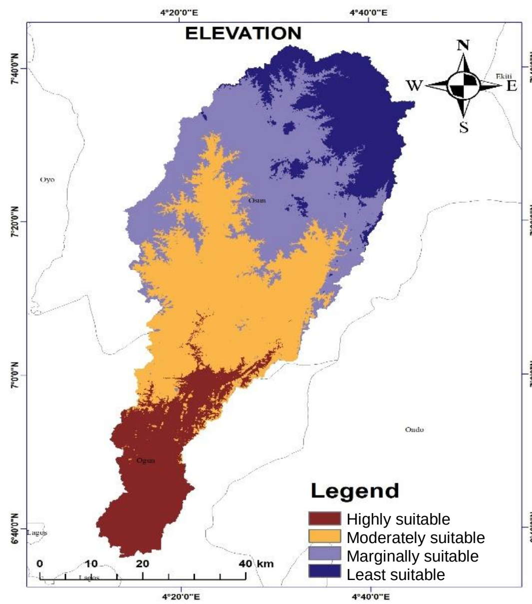


Figure 5: Elevation of the study area.

Highly suitable
Moderately suitable
Marginally suitable
Least suitable

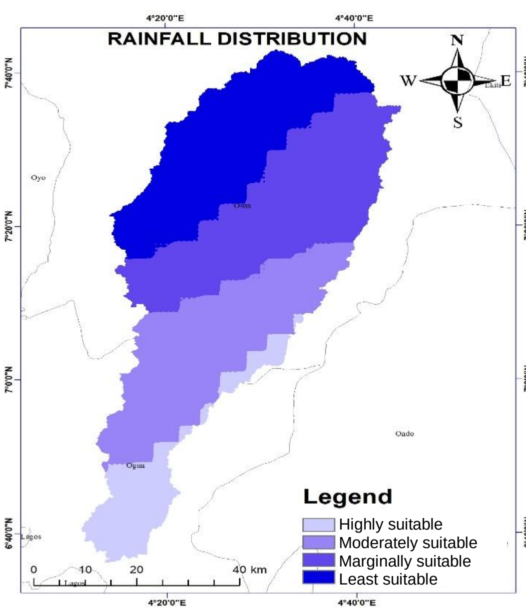


Figure 6: Rainfall distribution of the study

Therefore, the land suit… …erlaying 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 vary between 117 and 206 m.

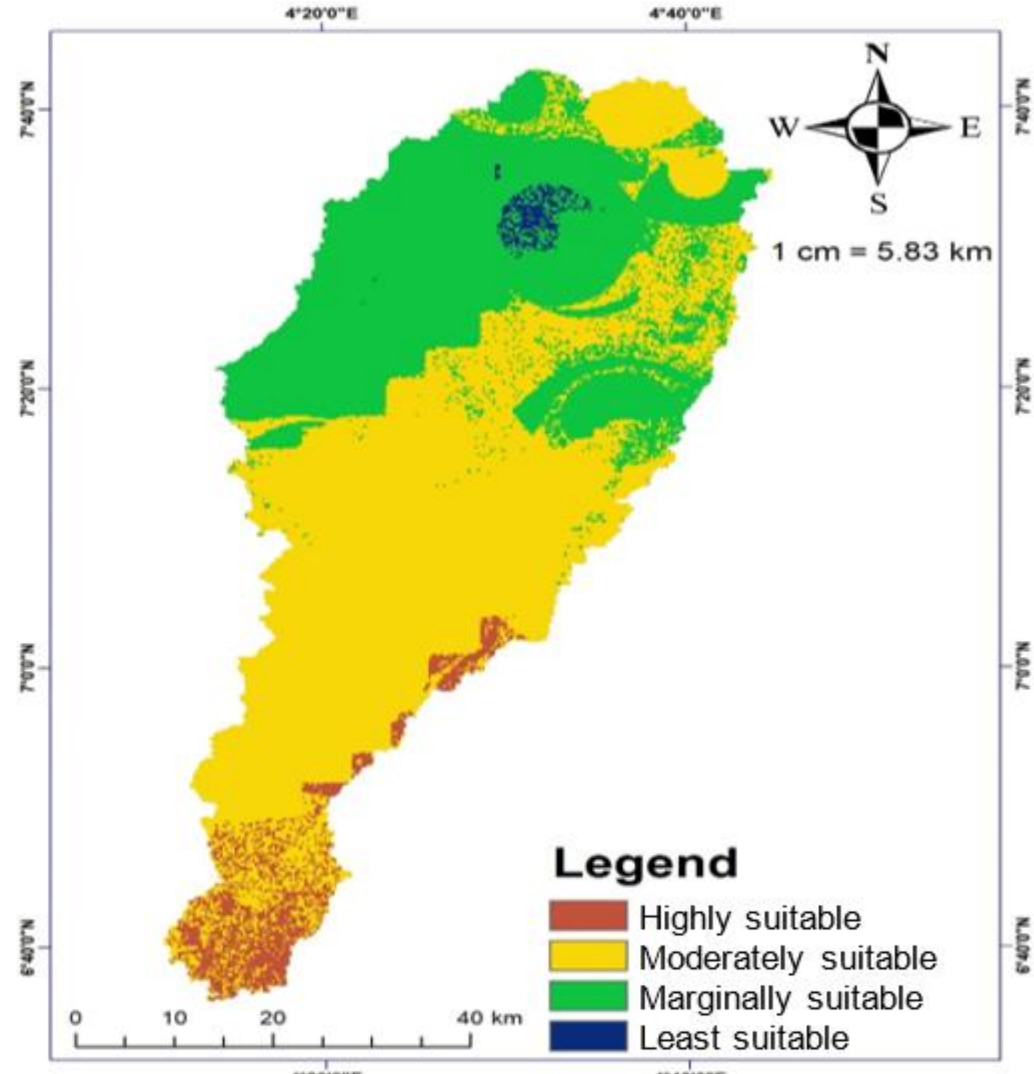


Figure 7: Maize suitable map of the study area.

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 km^2 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 where the age of respondents, size of land cultivated, maize output, and household size were examined under gender and years spent in school to understand the characteristics of respondents that belong to the group of farmers that 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,respondents spent in school. On the other hand, respondents who grew IMV had ages that varied between 52 and 72 years across gender and the ranges of years respondents spent in school. Across the gender of respondents who have spent more than 12 years in school, female respondents who cultivated IMV were the eldest (72 years) while the male counterpart was 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 spent in school, 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 and it was by female respondents who cultivated IMV and have more than 12 years in school. On the other hand, the largest area of land cultivated was observed among male respondents who cultivated IMV and spent between 6 to 12 years in school.

Among the IMV growers, the lowest maize output was discovered among female respondents who spent between 0 to 6 years in school. The highest maize output among IMV growers is 13833.33kg and this was discovered among male respondents who had more than 12 years of education. Across the years spent acquiring education in school and gender stratification as shown in Table 4, a difference of 2550 kg was observed between the lowest maize out of farmers who grew IMV and farmers who did not grow IMV. Similarly, a difference of 6166.66kg was observed in the highest maize output of IMV growers and non-IMV growers.

Across the years spent in acquiring education in school, gender, and grower of IMV or otherwise stratification, the household size varied between 3 and 6. The IMV grower had the least household size (3) and was headed by male respondents with more than 12 years ofacquiring education in school.

According to figures in Table 5, farmers who did not cultivate IMV and were members of the farmers' association had a 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 used 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

The figure 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. Interestingly, 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 were cultivating IMV but were not members of the association. Additionally, 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 (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 that would have been harvested if the enumerated farmers did not cultivate 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 that farmers would have harvested is 11695.8 kg. From the estimation presented in Table 6, 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 potential outcome of the adoption of IMV in area identified as suitable

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 .7082768	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. Table 6 shows aPOmean estimate of 0.6293833 that reveals the average potential outcome of cultivating IMV if all the farmers are not aware of IMV. On the other hand, if all the farmers are aware of its existence and availability, the potential estimate to cultivate IMV according to Table 6 is 0.5669662.

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 adoption of improved maize variety in the area identified as suitable

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

Among the sub-population of farmers who cultivated at least one IMV on suitable land on average would 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 responsible for farmers' use of IMV

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 a 35% chance of the farmer in the study area to cultivate IMV as the size of the land increases.

Table 8: Estimation of variables that influences the cultivation of IMVresponsible for cultivating 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
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

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

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.

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 of 60-61 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. 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 adopt the use of IMV. 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.

The study also found that farmers who cultivated IMV were small-scale farmers, except for those who grew maize on a medium scale and had between 6 and 12 years of schooling. This result demonstrates that farmers in the study area can cultivate more area of land and by extension increase their maize yield if they have access to suitable land. This outcome hintsatthe need to dismantle bottlenecks hindering farmers' ability to scale up maize cultivation on suitable land. And this is important given that Gebrehiwot *et al.* (2020) and De Groote *et al.* (2019), have 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 adopt improved varieties.

Interestingly, the study found that farmers who did not cultivate IMV had greater access to credit than those who did, indicating the need to establish a robust system of disbursing credit to farmers who applied, paying attention to farmers' input allocation and how resources are combined.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, resulting in 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 to understandthe scheme of events in the farming 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 Recommendation

This paper provided the suitability evaluation of land for maize cultivation using MCA and GIS techniques. It divulges the rate of cultivation of IMV and its determinants in the Owena Basin, which traverses Osun and Ogun states, Nigeria. The results of this study provide important implications for the development of services to help farmers operate sustainably and increase production by harnessing the comparative advantage of land for the cultivation of a particular crop type.

The study found that the moderately and marginally suitable land covers a larger area relative to the most suitable land. This hintsatan available opportunity to expand the area of land put to maize cultivation. Given that the total areas of land identified as being moderately and marginally suitable are high indicatestheneed for agronomic practices such as legume cultivation, and broadcasting of organic and inorganic materials to make the soil sustainably adequate to grow IMV. The cultivation of IMV was low among farmers who cultivated it on suitable farmland. Furthermore, being a member of an association where ideas are exchanged did not influence farmers to cultivate IMV despite the maize suitability status of their farmland.

The study revealed a fair mean potential outcome for IMV if all farmers cultivating on suitable land potentially cultivate IMV. Surprisingly, the general awareness about the existence of IMV was discovered to be higher among farmers who did not grow IMV compared to farmers who did cultivate IMV. Nevertheless, the effect of cultivating IMV on the output in the general sample was significantly more relative to farmers who did not cultivate it. Additionally, the effect of cultivating IMV within the sub-population of farmers who already cultivated IMV was lower when compared to the mean potential output. In other instances, the output was not different to zero. This hints at a gap in the allocation of resources in the cultivation of IMV, and this may require investigation. Furthermore, is instructive to ensure radical extension services engagement and support for farmers in the use of innovative technology like IMV. Besides, the integrationof other farming activities to cover an unforeseen negative event arising from insufficient knowledge/requirement to cultivate IMV on farmland with appropriate suitability status should be encouraged.

Furthermore, the size of the suitable land cultivated, along with farmers' access to extension services, was found to greatly influence the cultivation of IMV. Therefore, communicating the outcomes of this research with farmers and other stakeholders in the study area may aid their understanding of the capacity of their farmland in the cultivation of a particular crop and thereafter spur the use of necessary management practices to increase productivity while ensuring sustainable land use.

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