Sustainable Maize Crop Production in Owena Basin, Nigeria

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

Original Research Article

ABSTRACT

To improve maize production, efforts must be doubled to expand the current extent of land suitability profiling. Lingering questions hinged 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 initiatives to revitalize agriculture. Previous research addressed other crops rather than maize staples and assessed areas exclusive of the current study area. This paper used Geographical Information Systems (GIS) and Multicriteria Analysis (MCA) to map out land areas suitable for maize cultivation and further used frequency, counts, and parametric estimator to data from 466 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 farmers who did not

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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 cultivated IMV, and the size of land cultivated and access to extension services significantly (at P>|z|=0.000) contributed to 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.

1. INTRODUCTION

Research findings 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 [1], and its quality status to support farmers to double their production by cultivating higher-yielding IMVs [2]. 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 [3]. Nonetheless, reports from studies conducted by Bänziger et al. [4] and Tesfaye et al. [5] 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 [6] highlights the core of this research to improve the existing body of knowledge and enable impactful agricultural services that elevate farmers' productive capacity to the frontier.

Identifying a crop's essential niche is central to its optimal growth and development and promoting the adoption of improved crop varieties [7]. 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^2 that [8] has classified as arable, and mapping the land area per crop it best supports for optimal growth [9]. 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 from the same sector that contributes approximately 40% of the country's GDP and employs more than 65% of the national population [10].

Being a graminaceous C4 plant, maize (Zea mays L.) has a bundled secondary root system (at 50-70cm). The development of the 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 crop root [11], accordingly, facilitating optimal water, nutrient uptake, and solar radiation to enhance output per unit area [12]. Moreover, Nasri et al. [12] have advocated for the practice of intercropping legumes with maize. The aforementioned practice according to [13] and Rusinamhodzi et al. [14] 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 [15]. It is an affordable source of carbohydrates, vitamin B, protein, iron, and essential minerals Adeyeye et al. [16]. In assessing the importance of maize, Umar et al. [17] 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, [18] 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 [19]. In addition, this tonnage of maize 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 Ezeaku et al. [20].

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 [21,22]. According to [23], the multicriteria decision simplifies the problem of assigning weight to criteria participating in the land suitability evaluation Herzberg, et al. [24]. The multi-criteria technique, for example, has been employed for the Vulnerability Assessment and Household Preparedness Level to Flood (Balogun et al. [25]), Southwest Nigeria land use land cover evaluation [26], Spatial Market Distribution of the local market [27], Land suitability assessment for Cocoa (Kappo et al. [28]), land suitability for irrigation farming [29] and the citing of eco-tourism centers [30]. Other multicriteria approaches available for the same purpose include outranking methods, simple additive scoring Aldababseh et al. [31], Linear Combination, Simple limitation, fuzzy-logic modeling, Artificial Neural Networks, and the Analytical Hierarchy Process (AHP) [32], Ayla et al. [33], Alilou et al. [34], Herzberg, et al. [24]. Despite the availability of other land evaluation methods, the AHP appears to be the most employed in composite decision-making of land suitability evaluation Ghobadi et al. [35,36]. AHP's fundamental 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. [37].

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 [38]. makes the result of land assessment reliable for policy formulation. Thus, [39] 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. [24] also acknowledged the scientific effort of Sys et al. [40] towards gathering reference values required to plant fifty physical crops common to the tropical and sub-tropical regions of the world. While this information assisted some land suitability evaluation processes others questioned the comprehensiveness and thus, found it unsuitable for their local environment [41,42,43]. Additional information or adjustments were made to the document to fit their local environment (Boje et al. [44], Cools et al. [45]). This underscores the importance of local information in deciding what land can be used for and by extension illuminating the usefulness of the AHP method to this research [46,24].

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 Owena Basin, 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 Multicriteria Analysis (MCA) 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.

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 completely falls 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 millimeters (5.57 inches) of rainfall annually.

2.2 Data and Methods

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

2.2.1 Data requirement for spatial analysis

As atmospheric changes occurring across the globe impact more aspects of human life, geospatial evaluation, and its outcome would play a more crucial role in formulating and implementing policies that aim to mitigate uncomfortable occurrences. The data features (rainfall, soil fertility, soil structure, slope, and elevation) summarized in Table 1 were integrated using a multicriteria technique to map the different suitability statuses of the land in the study area in order to cultivate maize.

Fig. 1. Map of the study area

Table 1. Description of spatial data

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

Source: Authors' compilation

These features identified and integrated into this research work are supported by Tashayo et al. [47], Peter et al. [48], and Abegunde et al. [49]. Therefore, the integration of the layers using the multi-criteria assessment is achieved 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 [50]. 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 outcome 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 is 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 [51] principles (See Table 2).

The pairwise comparison matrix of the features is presented in Table 3 along with the weight assigned to them. The pairwise comparison process pairs two features at a time and according priority to 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. The same process is discontinued where the CR is greater than 10% [52]. The mathematical representation is given as follows;

$$CR = \frac{CI}{RI} \qquad (1)$$

$$CR = \frac{x-n}{n-1} \qquad (2)$$

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. This result gave a strong ground to continue the weight assignment to each of the features Balogun et al. [25]. A weighted overlay was carried out to map out the 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 [53]. As such, existing literature revealed that many researchers (Abdullah et al. [54], Antwi et al. [55], Pachemska et al. [56]) have employed AHP for different consistent land evaluation purposes. On the other hand, the literature also has other multi-criteria methods that could be employed for land evaluation among which are Artificial Neural networks [32]; simple additive scoring (Aldababseh et al.[31], Alilou et al. [34]), and Linear combination and developing fuzzy-logic as reported by Balogun et al. [25].

Table 2. 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 another
5	Strong importance	Experience and judgment strongly favour one element over another
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

Table 3. Pairwise comparison matrix

	Rainfall	Soil Fertility	Soil texture	Slope	Elevation	Eigen Vector
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 farmland of farmers who cultivated maize and who allowed the team to take the soil 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 development 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 technique overlays the raster of nutrient elements, multiplying each by an assigned weight and subsequently summing the elements together to create a soil fertility map. An important procedure in the weighted sum that this research employed is that all the rasters of the nutrient elements inputted and multiplied have the same weight which equals 1. A reclassification into 4 four classes of highly fertile, moderately fertile, marginally fertile, and least fertile followed this procedure.

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,

because the spatial analysis of land suitability is carried out before the enumeration of respondents cultivating maize on suitable land, we focused on three of the four identified suitability strata: suitable, moderately suitable, and marginally suitable for maize cultivation. The fourth stratum is the least suitable land area thus, it was excluded. The researchers liaised with the Farmers Association of Nigeria (FAN) in each stratum and administered 750 structured questionnaires to farmers in suitable areas over a four-month period (March to June 2021). Each stratum was allocated 250 questionnaires. A total of 466 questionnaires were gathered, 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 the questions were unanswered.

The primary data gathered from farmers to achieve the study objectives includes 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. 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.

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) [57] gives theoretical support to this research. The theory's applicability draws from the existence of several improved maize developed to help farmers improve harvest under varying growing conditions. In addition, the framework avails the estimation of farmers who did not cultivate IMV and the cultivation rate among farmers who cultivated the improved seed.

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

The potential outcome means (POMs), average treatment effect (ATE), and the average treatment effect on the treated (ATET) are parameters 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 cultivation level, 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 cultivation level 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 (cultivation of 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

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

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 [58,59]. 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;

$$E(y1x) = P(y = 1) = P \qquad (9)$$

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

$$0 \le P \le 1$$

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

$$0 \le \left(\frac{P}{1-P}\right) \le \infty \qquad (10)$$

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

$$-\infty \le ln\left(\frac{P}{1-P}\right) \le \infty \qquad (11)$$

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

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

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

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

$$j = 1, 2, \dots, k$$

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

Equation 13 depicts the logistic regression where $\ln\left(\frac{P}{1-P}\right)$ refers to the transformed logit [59]. The logistic function in the graph below mirrors the logit regression model [59] where $f(z)$ can bring together $-\infty, +\infty$ to 0, 1 [58]. 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.

$$f(-\infty) = \frac{1}{1+e^{-(-\infty)}} = \frac{1}{1+e^{\infty}} = 1$$

$$f(+\infty) = \frac{1}{1+e^{-(+\infty)}} = \frac{1}{1+e^{-\infty}} = 1$$
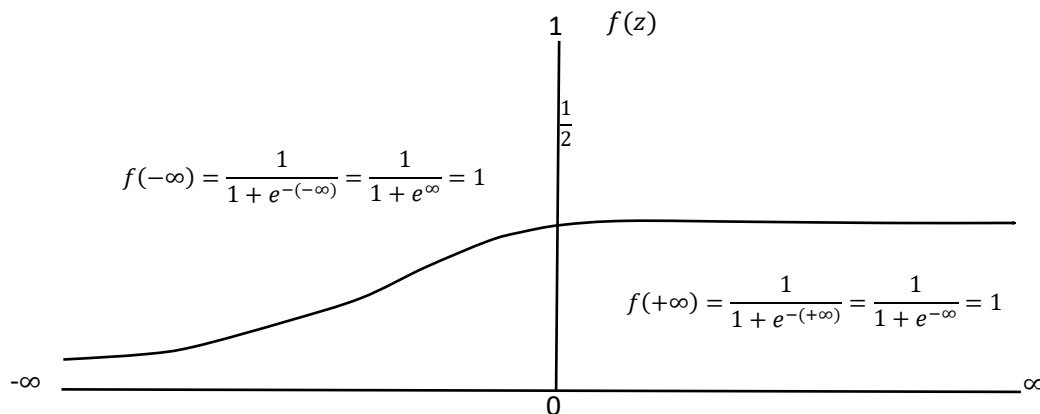
The choice of logistic function in regression estimation is premised on its equation range that is specified as

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

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

rather than the straight-line equation $y = b_0 + b_1 x_1 + e$.

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 [60]. The logistic regression also arranges regressors in a way that eases the variable isolation and prioritization.

3. RESULTS

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 share 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.

Consistent with 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 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.

Therefore, the land suitability map for maize cultivation was achieved by overlaying the reclassified raster images of the features earlier listed to generate the map shown in Fig. 7. As evidence in the map, the Highly suitable area of land spans over 180.46 km^2 (5.092634%). This area of land is characterized by rainfall of between 1486.75mm and 1571.84mm; loamy sand soil texture; a slope that varies between 0 and 3.23 degrees (0 and 5.76%) and elevation of between 0 and 117m.
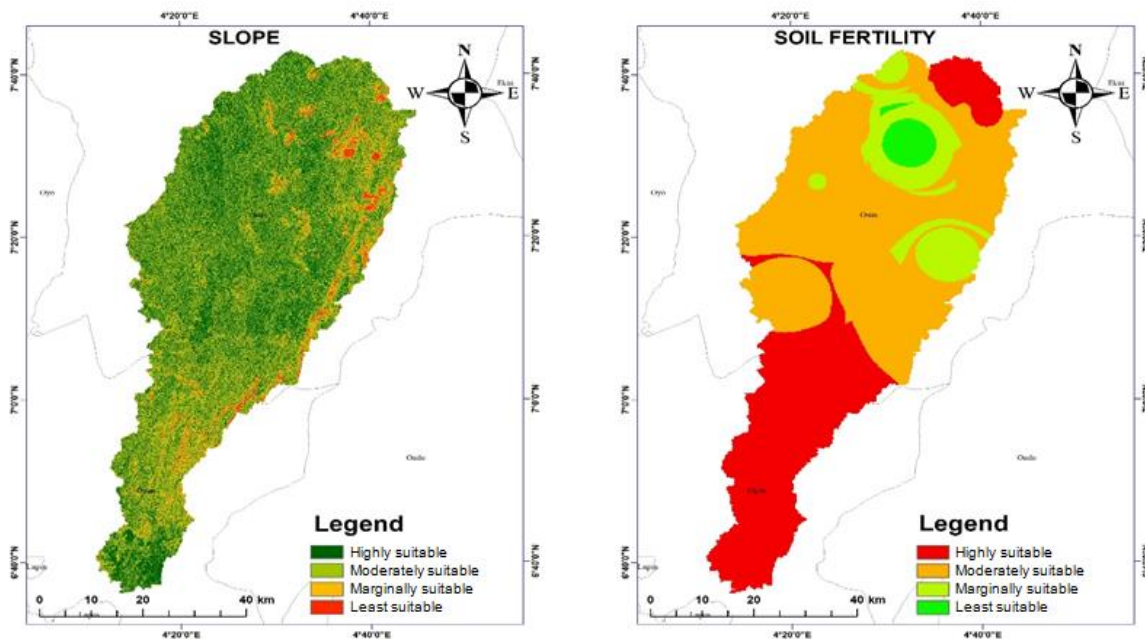

Fig. 2. Slope of the study; Fig. 3. Soil fertility of the study area

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.
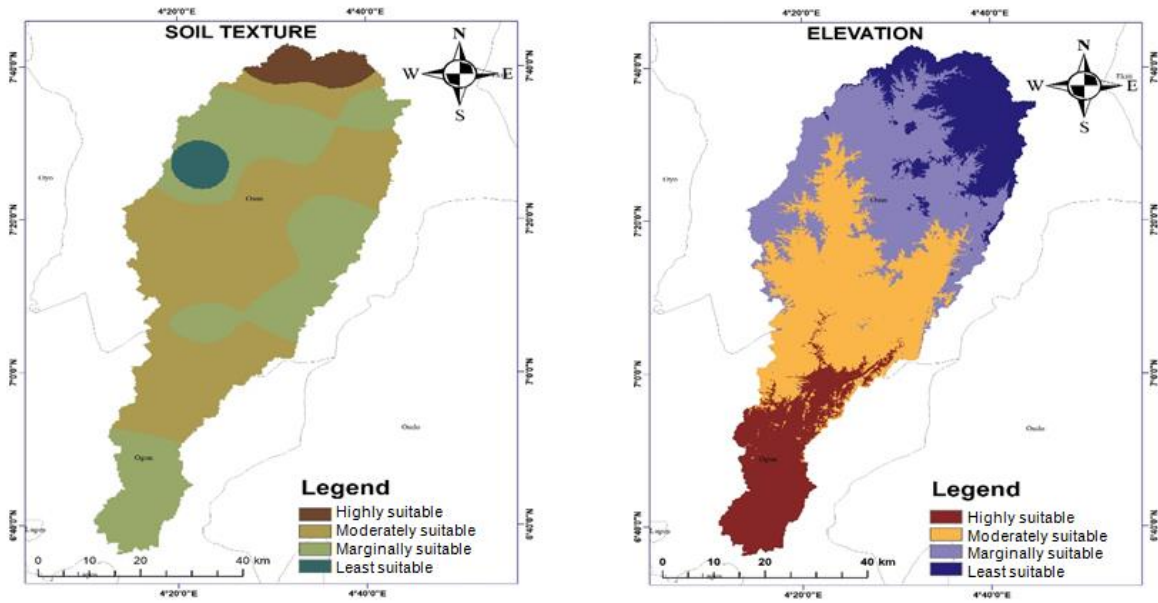

Fig. 4. Soil texture of the study; Fig. 5. Elevation of the study area
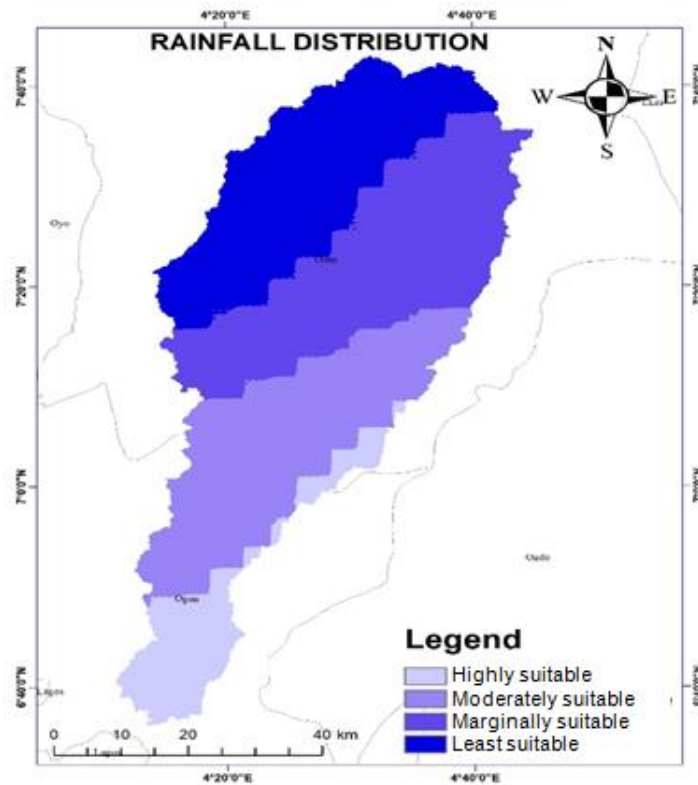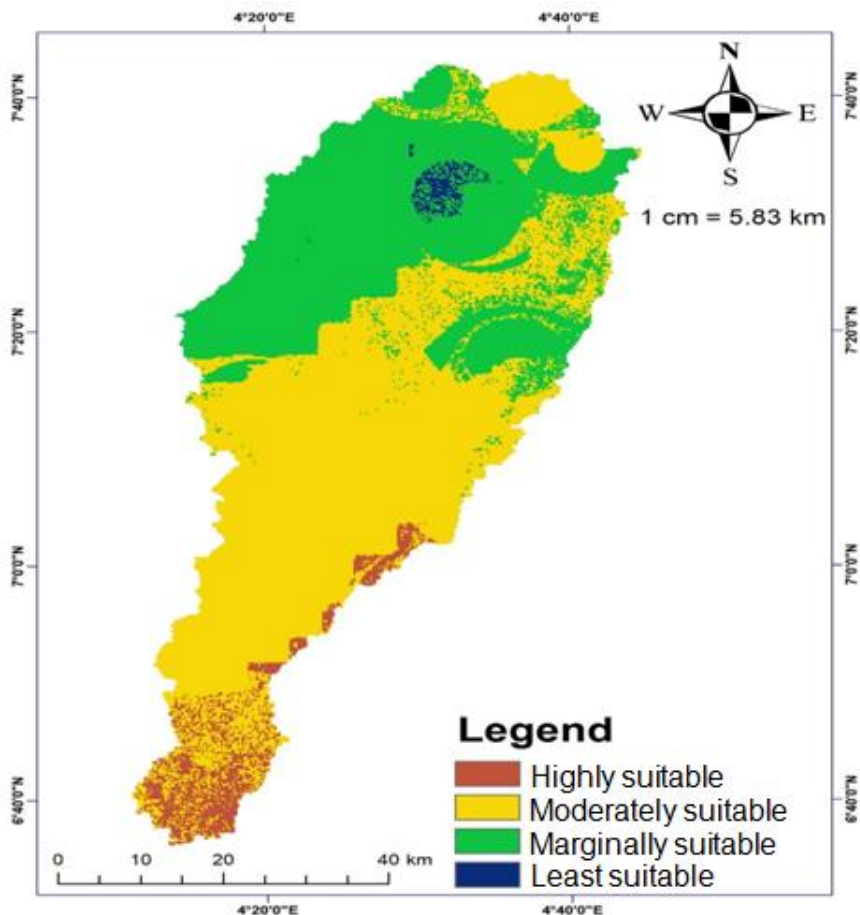

Fig. 6. Rainfall distribution of the study area

Fig 7. Maize suitability map of the study area

Furthermore, it was observed that 37.49% of the entire land, totaling 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 characterized 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.

3.1 Sociodemographic Description of Respondents Cultivating Maize on Suitable Land

Table 4 presents a cross-tabulation of variables in which the age of respondents, size of land cultivated, maize output, and household size

were examined under gender and years spent in school in order to understand the characteristics of respondents who belong to the group of farmers who cultivated IMV and those that did not cultivate IMV in the study area. As indicated in the Table, the age range of non-IMV growers varied between 50 and 61 for both males and females and across the ranges of years respondents spent schooling. On the other hand, respondents who grew IMV had their ages varying 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.

In addition, the result revealed that across the classes of years that respondents spent schooling, 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 which was 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 and completed between 6 to 12 years of formal education.

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

Across the years spent in acquiring formal education, gender, and grower of IMV or farmers who did not IMV 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 of formal education.

According to the figures in Table 5, respondents who 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.

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.

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

3.2 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 farmland or if they did cultivate IMV. The POmean estimate of 8127.703 kg was observed as the average maize output that 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 output that 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.

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 has a 0.5669662 chance of causing them to continue cultivating IMV or cultivate another IMV.

Table 5. 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 Pioneer P1359 or P1185	-	-	5	6

Source: Authors' compilation from field survey, 2021

Table 6. The PO of respondents cultivating IMV in the area identified as suitable for maize cultivation

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

The ATE estimate presented in Table 7 reveals 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.

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.

3.3 Estimation of Factors Influencing Farmers to Cultivate IMV

The logistic regression estimation presented in Table 8 reveals 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 least a 35% chance that farmers in the study area would cultivate IMV as the size of the land increases.

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 cultivating 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.

Table 7. Effect of cultivating IMV in the area identified as suitable for 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

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
Cultivated size 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. (***p<0.01)*

4. 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 these researchers are Alhassan et al. [61,62], Kumar et al. [63], and Adeyemo et al. [64]. 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 [65,66,67]. 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. [68], Mulugeta et al. [69] and [70] 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 high weight, followed by slope and elevation, as specified in Table 3. In the study area, soil texture is important in optimal plant germination because 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 [71] and Chukwudi et al. [72].

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. [73]), which is critical for achieving optimal crop production. Slope also affects the process of mechanization (Tashayo et al. [47]) but can be beneficial when soil is transferred from higher to lower positions, creating a C-rich reservoir [74]. However, the aforementioned beneficial effect can counterbalance the loss of gases of other larger nutrient components in the greenhouse gas balance Henault et al. [75].

The elevation or altitude of the land plays a key 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. [76]. A high or low elevation determines the intensity of sunlight that drives the photosynthetic process, which fuels optimal crop growth and eventual yield [77].

According to the study, farmers who did not cultivate IMV are older, with an age varying between 60 and 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 about farming customs and practices, that they used to over the years. This position aligns with the observation of Udimal et al. [78] documented in their article where older farmers showed 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. [79] 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 mostly small-scale farmers. Given that a large expanse of land (classified as highly, moderately, and marginally) has been identified as suitable for maize cultivation illuminates 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 hints at a system that 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. [80] and De Groote et al. [81], reported a positive relationship between the use of improved varieties and farmers with larger land holdings. Although [82], 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 [83], 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. [84] and [85], 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 hints

that some farmers were unable to optimally allocate their input resources, causing a negative impact on their harvest. This finding contradicts those of [86] and highlights the need for additional information on the technical efficiency of farmers who cultivated IMV and farmers who did not in order to understand the scheme of events in the study area during their 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.

5. CONCLUSION AND RECOMMENDATION

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.

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.

CONSENT

As per international standards or university standards, respondents' written consent has been collected and preserved by the author(s).

COMPETING INTERESTS

The authors have declared that no competing interests exist.

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