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Article

A linear regression model to demonstrate balancing productivity and sustainability for small-scale farmers: A case study in Malawi

Oluwasegun Julius Aroba*, N'wa-Jama Mashele, Chifuniro Kandaya, Michael Rudolph

Centre for Ecological Intelligence, Faculty of Engineering and the Build Environment (FEBE), University of Johannesburg, Electrical and Electronic Engineering Science, Auckland Park Campus, Auckland Park, P.O. Box 524, Johannesburg 2006, South Africa
*** Corresponding author:** Oluwasegun Julius Aroba, Jaroba@uj.ac.za

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Abstract: Adverse climate change effects, specifically droughts, floods, and dry spells, negatively affect agricultural production. The application of several machine learning methods assists with crop production prediction while factoring in these environmental variables. Machine learning is a crucial tool to ensure crop yield estimation, good agricultural planning practices, and effective decision-making, enabling better application of proposed interventions. Ecological intelligence signifies a paradigm shift toward balancing the competing goals of sustainability and productivity. This study aimed to demonstrate efficient agricultural productivity that addresses SDGs 12 (Responsible consumption and production), SDG 13 (Climate action), and SDG 15 (Life on land). The study was carried out in Lilongwe and Dowa districts, Malawi, and compared single and dual crop yields of farmers cultivating the same crop on similar hectarage, and their respective crop value, profitability, and sustainability. The study population comprised 62 (29.7%) male and 140 (70.3%) female farmers. A linear regression model analysis showed the importance and value of both crop yield and ecosystem resilience. The 80:20 train-test ratio split was used to produce good and effective output. Results showed that the dual crop yields of maize and beans were more profitable in comparison to both monocrop beans and maize plots. Male farmers had higher profits and yields than female farmers. These results show that sustainable practices can be incorporated into farming systems and could ensure both profitability and sustainability. However, future research will be done using intensive multiple-cropping and environmentally friendly methods that focus on consistent yields over an extended period.

Keywords: crop yield estimations; machine learning; productivity; small-scale farmers; sustainable agroecological practices; sustainable development goals

1. Introduction

The primary aim of most farmers, regardless of scale and enterprise, is to achieve high productivity. A farm's efficiency is usually measured according to productivity and economic performance [1,2]. Production refers to the quantitative ratio of outputs to inputs of any planted crop in each area or field. Several studies have shown that there is a trade-off between high-productivity practices and sustainable practices [3–6]. This trade-off presents farmers with two choices: prioritize productivity, using intensive monocropping with chemical fertilisers and pesticides to achieve high yields, or use production methods that are more natural and focus on environmental regeneration and consistent yields over an extended period [7,8]. Choosing monetary gains over environmental responsibility makes farmers more susceptible to adverse climatic conditions and creates a gap in addressing some of the Sustainable Development Goals (SDGs) [4,9]. Systems that are driven by productivity often have adverse environmental effects such as biodiversity loss, reduced soil biota, soil degradation and erosion, greenhouse gas emissions, and water contamination [10–12].

For Sub-Saharan Africa (SSA) regions, a large percentage of the population depends on agriculture for food, livelihoods, and employment. SSA countries depend on maize as a staple crop, with over 40 million ha under maize cultivation [1,13–16]. Most of these farmers are under-resourced and heavily affected by climate and environmental disruptions, indicative of the need to adopt sustainable production methods [7,13,17,18]. Agricultural projections for Africa show that production must increase by 60% to 110% to feed the population by the year 2050 [5,18]. This places immense pressure on farmers to intensify their production systems [1,19].

About 60% of the agricultural land is utilised by 2.5 billion small-scale farmers (SSF) who usually own or have access to less than 2 hectares of land, and use rain-fed subsistence farming practices based on limited inputs and have low bargaining power. Furthermore, they have limited financial resources and minimal market and climate information [20–22]. The regions with the highest number of SSF are Asia, India, and SSA [5,23,24]. This factor poses two interlinked problems; the populations are projected to rise in these regions, but this is also where climate vulnerability and food insecurity are rife [2]. Climate change directly affects agriculture, resulting in food shortages and reduced productivity, thus necessitating the adoption of resilient production methods. In SSA, 66% of the agrifood systems employment is occupied by women. Female farmers are much more likely to adopt climate-smart agricultural techniques. However, they face more challenges, such as limited access to inputs and technology, funding, land ownership, and information, than their male counterparts. Furthermore, women farmers are also more severely affected by climate disasters and food insecurity than male farmers [16,26–28]. Given ample support through policies and resources, women have the potential to be as productive as male farmers [26–28].

The food system, specifically food production, faces many challenges that have dire consequences for both people and the environment. The agricultural industrial revolution prioritised high-income gains at the expense of the environment. This has created a problem wherein a large portion of arable land has become depleted of both structure and fertility due to the overuse of chemical inputs in the pursuit of high yields. These practices are unsustainable, and in response, several countries have drafted various frameworks to guide the adoption and implementation of climate-resilient farming systems.

This research aims to showcase how precision agriculture's predictive capabilities can be used to inform decision-makers regarding adopting climate-smart agricultural techniques. The study presents how Malawi farmers navigate decisions regarding environmental preservation versus profitability. The study demonstrates efficient agricultural productivity that addresses SDGs 12 (Responsible consumption and production) by showing that sustainable agroecological techniques that mitigate against adverse climatic conditions, SDG 13 (Climate Action), can help farmers reach profitability without sacrificing the environment and thus improve SDG 15 (Life on land). Firstly, the literature review is presented. Secondly, the research design, materials, and methods are outlined. The third section presents the results and discussion. The final section gives the concluding remarks.

2. Literature review

2.1. Transitioning small-scale farmers in Malawi towards sustainable practices

Since independence, 60 years ago, agriculture has played a central role in defining Malawian rural livelihoods [25,29]. These authors report that the sector employs over 85% of the rural population and contributes about 35% to 40% to the gross domestic product (GDP). Furthermore, they contribute over 90% to total export earnings. Malawi's agricultural sector is dominated by smallholder farmers who live in rural areas and cultivate low-input rain-fed systems on an average of 0.7 ha of land [25,30]. However, the country's economy depends largely on how its smallholder farmers perform. Smallholder farmers account for over 75% of food consumed in Malawi [31]. The rainfall pattern and access to farm inputs largely determine the food security and livelihoods of most of the population [29,32]. Maize is the primary crop in Malawi, where SSF rely on single-crop farming (**Figure 1**) for food security, leaving them vulnerable to climate change effects. Smallholder farmers consume 60% of the field that they cultivate [32,33].

Agriculture relies on diverse natural resources to enhance and ensure productivity; however, ongoing climate change shocks and instability threaten and undermine their viability. Malawi co-signed the United Nations Framework Convention on Climate Change (UNFCCC). The UNFCCC, an entity of the United Nations, is commissioned to support the global response to Climate change. Malawi drafted its National Climate Change Framework Policy (NCCMP) to align with UNFCCC and guide national actions to mitigate anthropogenic interference with climatic systems. The overarching goal of the policy is "*To promote climate change adaptation, mitigation, technology transfer and capacity building for sustainable livelihoods through Green Economy measures for Malawi*" [26]. Through this policy, Malawi aims to facilitate the adoption of production methods that are climate resilient. One of these methods is agroecology, which has a variety of practices that promote sustainable and

Figure 1. Dowa small-scale maize farmer in Central District, Malawi (author's own construct).

resilient agricultural systems. Agroecology represents a holistic and interdisciplinary approach that integrates ecological principles and practices into agricultural systems [34–36]. Through its various practices such as intercropping, crop rotations, cover cropping, green manure, and reduced tillage, it underscores the importance of biodiversity, ecological processes, and local knowledge in enhancing productivity, resilience, and sustainability [2,3,7,8,35].

Intercropping, one of the practices highlighted in this research, promotes a more diversified plant community, enabling complementary and facilitative relationships. However, in most cases, farmers still follow monocropping systems for various reasons, including a lack of resources, technical training, and decision-making power [27,28]. The NCCMP aims to reduce the socio-economic and environmental vulnerability of farmers caused by climatic extremes [26] and thus needs to clearly outline and educate farmers about alternative methods that bolster environmental sustainability whilst ensuring productivity.

Three of the SDGs, 12 (Responsible consumption and production), 13 (Climate action), and 15 (Life on land) are intrinsically linked to agricultural production and food systems [17,19]. The study aims to show that adopting agroecological practices and techniques such as dual cropping can improve a system's resilience against climate change, lead to both profitability and sustainability, which will enhance the livelihoods of those living off the land.

Machine learning techniques are applied in various fields, such as predicting customer phone usage and evaluating customer behaviour in supermarkets. Agriculture has been using machine learning for several years. One of the more difficult issues in precision agriculture is predicting crop yield, and numerous models have been put forth and proven effective thus far [38–41]. Several datasets must be used to solve this problem, since crop output is influenced by various variables, including soil, weather, fertilizer use, and seed variety [38,42]. This suggests that predicting agricultural production involves many intricate procedures and is not a simple operation. Although crop yield prediction models nowadays are capable of accurately estimating the actual yield, improved yield prediction performance is still preferred [43,44].

2.2. Productivity vs. Sustainability: Results from small-scale farmer experiments

Several studies compared conventional farming techniques to agroecological farming techniques. Studies showed that intercropping legumes and maize resulted in desirable yields and improved soil structure and health, thus boosting the systems' resilience. Intercropping, especially with legumes, is affordable for soil rehabilitation due to their nitrogen-fixing capabilities [13,45,46]. Study [12] focused on soil health and the various agroecological practices that lead to the restoration and maintenance of healthy soils. This is important as soil is a major determinant of crop nutrition and growth. However, it is increasingly being lost due to malpractice, reducing the amount of arable land. Others highlighted that fields planted under organic farming have lower yields than conventional fields. Nevertheless, organic fields gradually build up core organic matter and carbon, enhancing their ability to retain moisture and withstand harsh climatic conditions [47,48]. Further emphasis was placed on the adoption of sustainable practices will require institutional support targeting farmer education, socio-economic interventions, and technology [48]. This evidence should prompt policymakers to be proactive in working with farmers to ensure that the SDGs related to agricultural production are met by farmers.

A common finding was the time factor; it takes some time to see tangible environmental benefits when using agroecological farming techniques. Because of the damage to the ecology caused by constant and intensive application of chemical inputs, restoration takes time but offers an important balance between productivity and sustainability. The most extensive study identified over a million SSF in China whose agricultural practices ensured both high yields and environmental sustainability [5]. The researchers developed a decision support software called Integrated Soil-Crop Management (ISSM) that identified strategies specific to the different agroecological zones where the participant farmers were located. This research was a collaborative process between researchers, extension officers, community engagement officials, policymakers, agribusiness, farmers, and funders, highlighting the need and strength of collaboration. The duration of the research allowed for learning, engagements, reiterations, and modifications of approaches until synergy was obtained in the project. Such interventions are needed for the SSF groups [5].

3. Materials and methods

The study compared single and dual crop yield differences of farmers cultivating the same crop and hectarage, and their respective crop value, profitability, and sustainability. The study was carried out in Lilongwe and Dowa, Malawi (**Figures 2 and 3**), and used a sample of 204 farmers who benefited from the *Cultivate Project Farmers* from 2020 to 2023. The distance between Dowa and Lilongwe is approximately 68 km, which is 40 min by car.

A key barrier to raising the agricultural output of these smallholder, maize-based farming systems in Malawi and other eastern African countries is poor and falling soil fertility. Through a "Risk Management Project," which operated from 1998 to 2004, smallholder farmers in central Malawi were introduced to a variety of yearly rotation or intercrop technologies. At an elevation of 1240 m above sea level, Dowa, Lilongwe District, is located inside the Kasungu mid-altitude plain at 13° 32′ S and 33° 31′ E as shown in **Figures 2 and 3**. 95% of the land in the area is suited for agriculture, which dominates livelihood methods. However, as Chisepo's population has grown, continual farming in nutrient-depleted fields has become the norm. Although maize is the most cultivated food crop, farmers sometimes cultivate other crops, such as regional types of common beans [30].

A linear regression model analysis was used to show the importance and value of both crop yield and ecosystem resilience. It applied cutting-edge machine learning and precision farming by drawing on multiple factors, such as crop yield prediction based on historical data, soil conditions, and weather patterns, allowing farmers to plan better optimization of resource management. For comparing monocropping

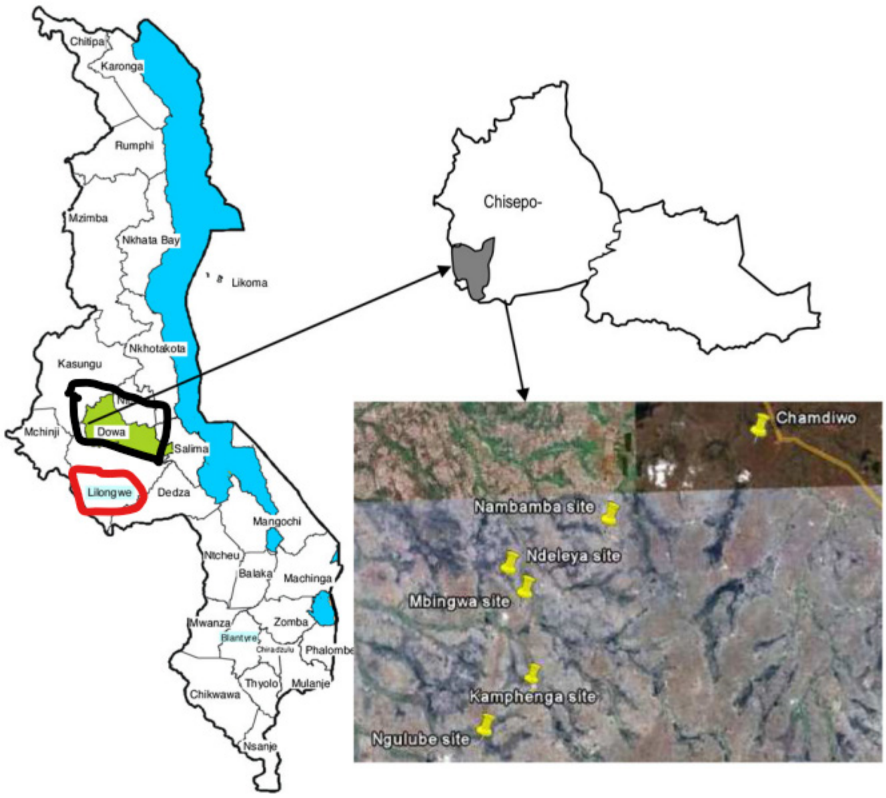

Figure 2. Map of Dowa and Lilongwe, Malawi (author's own construct).

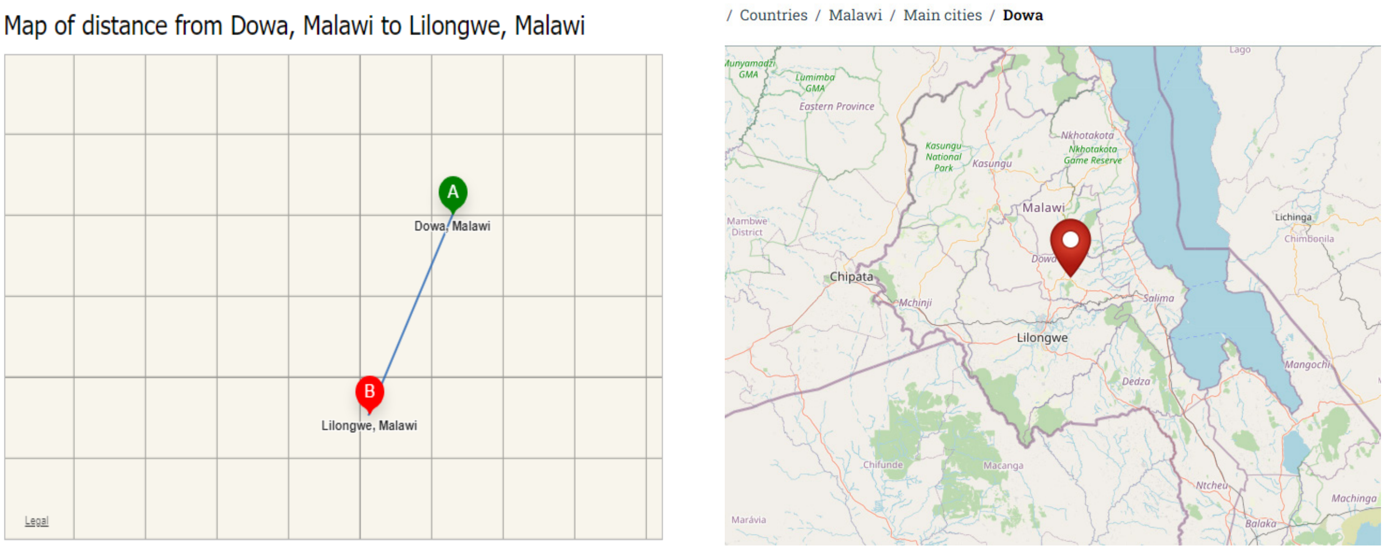

Figure 3. Distance between Dowa and Lilongwe on the Map (author's own construct).

and intercropping techniques in terms of promoting productivity among smallholder farmers amid climate change shocks.

3.1. Machine learning model

A machine learning model (random forest classifier, linear regression) was deployed to determine the crop selection, mean square error, and accuracy score to achieve the comparison of single and dual cropping. The 80:20 rule, which is train

train-test ratios split, was used to produce good and effective output. The 80:20% ratio has proven to be effective for machine learning models [49]. The study was conducted under the jurisdiction of the Centre of Ecological Intelligence (CEI) at The University of Johannesburg (UJ), which serves as the centralized project support Centre for SSF. The Python libraries used for the linear regression models are sklearn, StandardScaler, Scikit-learn, Numpy, Pandas, TensorFlow and Pytorch, and PyCaret.

Cultivation was implemented by a Malawian-based social enterprise organization called Charis Farms and Invest, with financial support from Operation Blessing, which served as one of the Centre for Ecological Intelligence centres in Malawi under the supervision of Mr Chifuniro Kandaya. The study was both qualitative and quantitative, and multiple methods for data collection were employed. Questionnaires and interviews were conducted among 202 farmers from Dowa and Lilongwe. The survey aimed to assess the crop yield per acre using the traditional practice of monocropping among smallholder farmers. From this data, a project was designed. One of the interventions included the distribution of bean seeds to the farmers to enhance the adoption of intercropping. After four months, a mid-survey was conducted. The goal was to assess the change in perception towards intercropping, the adoption rate, and the experiences of the farmers.

The study sought to analyse whether there were changes in crop yield per acre and income per household of the targeted farmers. The first data collection method for the study was focus group discussions. The main purpose of focus group research was to draw upon respondents' attitudes, feelings, beliefs, experiences, and reactions in a way that would not be feasible using other methods, such as observation, one-to-one interviewing, or questionnaire surveys. The process included collecting nonverbal information from the interaction and integrating it with verbal information from the conversation. The study identified farmers' group committee members as participants in the focus group discussions. The second data collection methodology for this study was in-depth interviews. 202 farmers were interviewed before and after the project. The general interview guide approach was employed to ensure that the same general areas of information were collected from each farmer.

Microsoft Excel was used for collecting, storing, and analysing the quantitative data. This included the number of kilograms produced by the farmers and the income generated. Every farmer signed consent forms designed by Charis Farms and Operation Blessing. The farmers accepted that their data would be used for publication and the media.

3.2. Crop prediction and data set

Machine learning techniques were used to predict crop yields using data from Lilongwe and Dowa. Four machine learning algorithms were employed. To obtain the most accurate crop prediction, these algorithms are also compared to find trends in the data, and it's applied to crop prediction. In this study, machine learning is used to forecast the yields of the two most commonly grown crops, beans and maize, in Malawi's Central District.

Table 1. The data set import table sample.

Name	0
Gender	0
District	0
Household Size	2
Rainfed Size of the Land (Acres)	0
Baseline rainfed (Maize) Kgs/yield 550Kgs/Acre	0
Maize Inputs per Acre	0
Baseline Maize Revenue	0
Profit	0
Unnamed: 10	202
Training Received by all farmers	189
Inputs received	196
dtype:	int64

Dowa and Lilongwe provided data related to farming from SSF that were aggregated by the Centre for Ecological Intelligence (CEI) Johannesburg. This data set consists of 204 SSF that cultivated both maize and beans, as shown in **Table 1**, and the sample of the data, as displayed in **Table 2** below.

Table 2. Data set sample after cleaning.

	Unnamed: 0	Name	Gender	District	Household Size	Size of the Land (Acres)	(Maize) Kgs\nYield 550Kgs/Acre	Maize Inputs per Acre	Baseline Mazize Revenue	Profit	Unnamed: 10	Training Received By all farmers	Inputs received
0	1	Vincement Wiliam	M	Dowa	4.0	5.0	2750	60000.0	275000	215000	NaN	1. In organic Fertliser Production. Soil mana...	1. Beans
1	2	Binalsoni Damalison	M	Dowa	6.0	6.0	3300	72000.0	330000	258000	NaN	2.Soya bean management	2. Sweet Potatoes
2	3	Maxwell Chalera	M	Dowa	7.0	8.0	4400	96000.0	440000	344000	NaN	3. Piggery management	3. Pigs
3	4	Zakeyo Teremu	M	Dowa	3.0	4.0	2200	48000.0	220000	172000	NaN	4. Cooperative formulation and management	4.Maize
4	5	Emerida Chalera	F	Dowa	2.0	3.0	1650	36000.0	165000	129000	NaN	5. Pest and disease identifciation and control	5. Rice

	Unnamed: 0	GENDER	DISTRICT	HOUSEHOLD SIZE	PLOT SIZE-RAINFED(ACRES)	BASELINE RAINFED MAIZE YD-550Kgs/Acre	MAIZE INPUT COST(Mwk)/ACRE	BASELINE MAIZE REVENUE(Mwk)	PROFIT(Mwk)
1	1.0	M	Dowa	4.0	5.0	2750.0	262500.0	275000.0	12500.0
2	2.0	M	Dowa	6.0	6.0	3300.0	315000.0	330000.0	15000.0
3	3.0	M	Dowa	7.0	8.0	4400.0	420000.0	440000.0	20000.0
4	4.0	M	Dowa	3.0	4.0	2200.0	210000.0	220000.0	10000.0
5	5.0	F	Dowa	2.0	3.0	1650.0	157500.0	165000.0	7500.0
...	...	...	...	...	...	...	...	...	...
198	201.0	F	Lilongwe	4.0	1.8	990.0	94500.0	99000.0	4500.0
199	202.0	F	Lilongwe	3.0	1.8	990.0	94500.0	99000.0	4500.0
200	203.0	F	Lilongwe	6.0	4.0	2200.0	210000.0	220000.0	10000.0
201	204.0	M	Lilongwe	5.0	2.2	1210.0	115500.0	121000.0	5500.0
202	204.0	M	Lilongwe	5.0	4.5	2475.0	236250.0	247500.0	11250.0

202 rows × 9 columns

3.2.1. Data preprocessing

A linear regression model was used to model the dataset. The crop yield using the machine learning models, which included data pre-processing to ensure that the dataset is clean, standardized, and suitable for training and testing the machine learning models. The dataset was loaded into a Panda DataFrame from a CSV file, which was then checked for any missing values. once the publicly accessible repositories have been searched for data. Data frames can be combined based on shared columns once the data cleaning procedure is finished. In order to keep all of the qualities on the SSF, normalization is also necessary. The item (crop), country, year, yield value, average rainfall, pesticides, and average temperature are anticipated to be the final aspects in the data frames. It was observed that certain features had missing values, represented as zeros. x_i represents an individual value in a column.

$\bar{x}$ represents the mean of the non-missing values in that column.

$x_i^{'}$ represents the value after imputation.

For a column with missing values, mean imputation can be described with the following equation:

$$\begin{cases} x_i \; if \; x_i \neq NaN & (1) \\ \bar{x} \; if \; x_i = NaN & (2) \end{cases}$$

where:

$$\bar{x} = \frac{1}{N}\sum_{j=1}^{N} x_j \tag{3}$$

N is the number of non-missing values in the column.

After splitting the data, the features were standardized to confirm that every attribute contributed equitably to the model's performance. The sklearn library's StandardScaler was used to modify the features of metrics, giving them a mean of zero and a standard deviation of one, making the data suitably ready for training the selected machine learning models. The formula for standardization is given in Equation (1).

$$sv = \frac{ov - m}{sd} \tag{4}$$

where:
sv = standardized value
ov = original value
m = mean
sd = standard deviation

3.2.2. Linear regression

R-squared (R^2) Score: 1.0

Mean Squared Error: 0.0007317073170731655

The study adopted three well-known performance evaluation metrics, which are mean absolute error, mean squared error, and root mean square error. The metrics were implemented to raise prediction rating accuracy. Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are two commonly used metrics for eval-

Table 3. Performance evaluation metrics.

The Mean Absolute Error (MAE)	5.740665395622761e-16
Mean Squared Error (MSE)	5.772152965031794e-31
Root Mean Squared Error (RMSE)	7.597468634375395e-16

uating the performance of regression models. RMSE and MAE complement each other, providing a comprehensive understanding of a model's performance by highlighting different aspects of the prediction errors. It is often useful to report a complete picture of the model's accuracy and reliability (50).

Table 3 presents the performance evaluation metrics for the linear regression model in predicting maize and bean crops.

4. Results and discussion

The development of the model was with sklearn, Seaborn, matplotlib, and matplotlib sklearn. ensemble. linear_model and Pre-processing by sklearn. preprocessing, nltk, nltokenize, corpus. After cleaning and exploring the relationship between the features, the final data frame that contains all the features that will be used for the prediction process can be seen below in **Figure 4**.

The Dowa and Lilongwe Central districts have a higher proportion of adult female farmers than adult male farmers [51]. **Figure 4** of small-scale farmers in the Dowa and Lilongwe communities is 202 in population, and the males are 62 and females 140.

Figures 5–11 present the data representation for the density plot of the gender of male vs female, the density plot of house size, baseline rainfed maize, maize input cost per acre, the baseline for maize revenue, crop yield log, and profit.

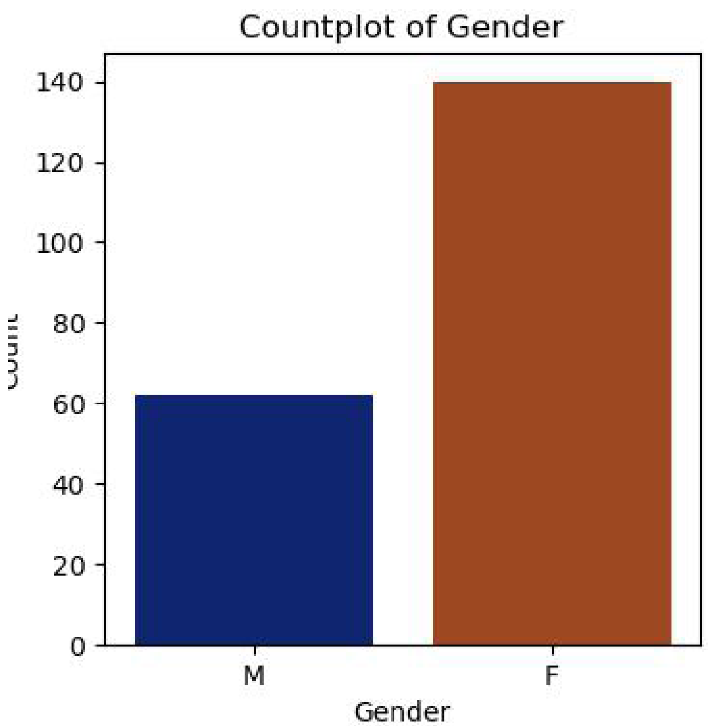

Figure 4. Number of small-scale farmers in Dowa and Lilongwe District by gender.

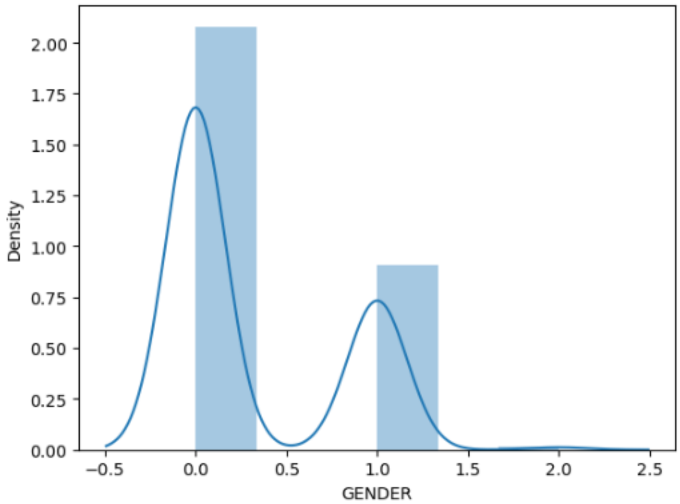

Figure 5. Density plot by gender.

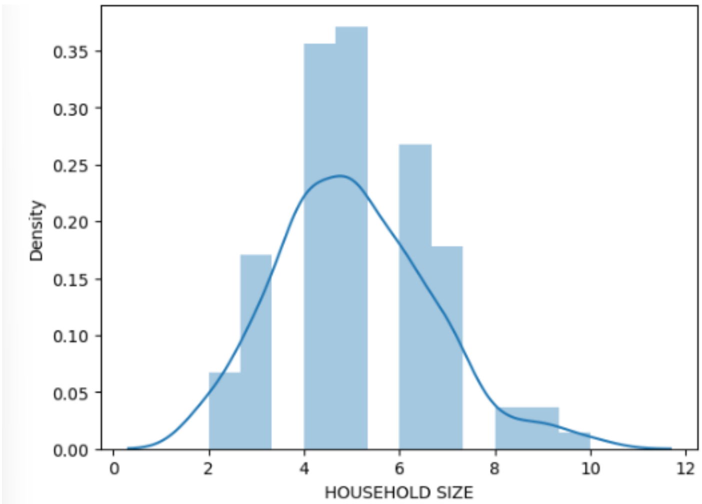

Figure 6. Density plot by household size.

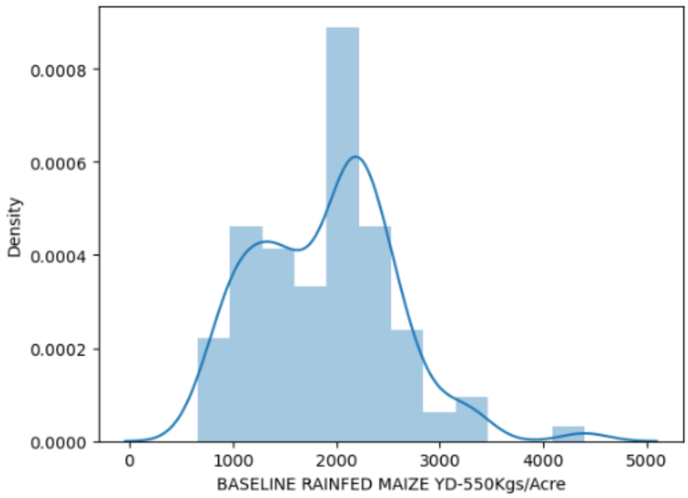

Figure 7. Baseline rainfed maize.

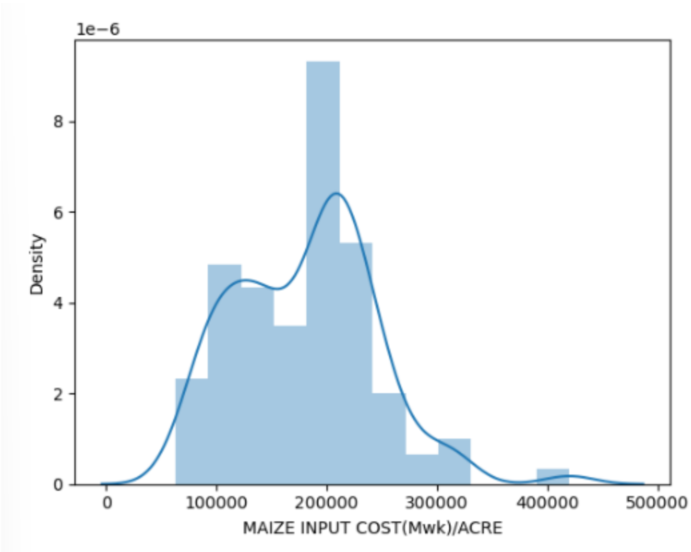

Figure 8. Maize input cost/acre.

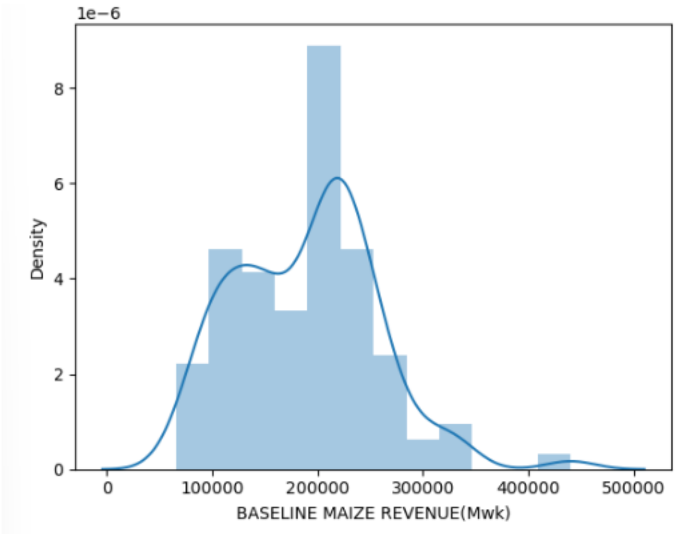

Figure 9. Baseline for maize revenue.

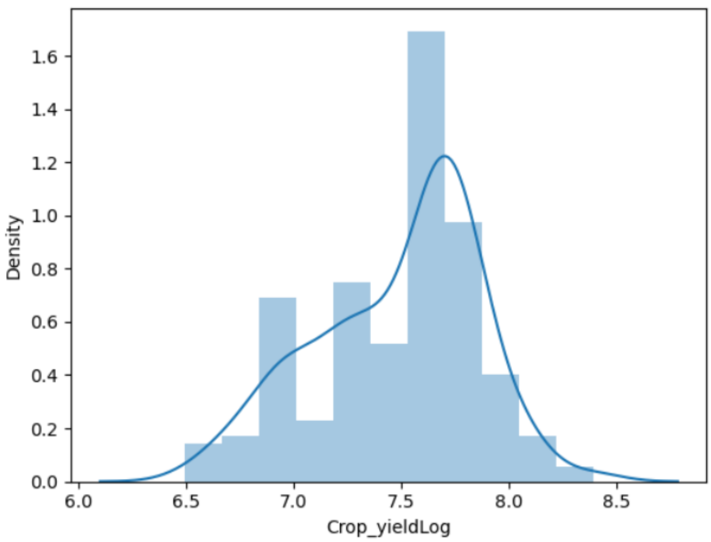

Figure 10. Crop yield log.

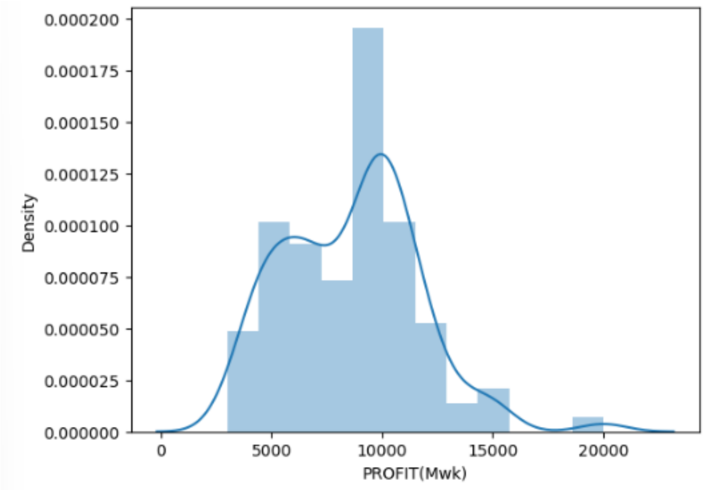

Figure 11. Baseline rainfed maize profit.

The two regions had a higher rate of women farmers than male farmers. However, the yields and profits made by the female farmers were less than those of their male counterparts due to a myriad of challenges. Female farmers have limited access to credit, inputs and resources, technical and extension services [16,52]. Furthermore, they have limited control over the land which they cultivate [25,53,54]. Such factors limit these farmers' decision-making powers, impacting their ability to plan and utilize the farmland as they see appropriate. Research shows that an investment in women farmers can drastically improve their profitability [27,28]. The monocrop maize plots had the lowest yield compared to the monocrop bean and the dual crop system. This can be attributed to the fact that maize is a heavy feeder, and continuous planting on an already nutrient-low soil without any rehabilitative measures is not sustainable [4,7]. Such practices negatively impact environmental resilience and further compound the economic vulnerability of the farmers. The plots sown for beans were three times higher than the maize yields. Beans are part of the legume family and have soil-building characteristics. Legumes have beneficial effects on the soil's physical, biological, and chemical structures. They enhance the soil's ability to adsorb nitrogen and make it available to plants [11,55]. This explains why the field planned with both maize and beans outperformed the other fields. The legumes created a nutrient-rich environment for the maize and increased water availability by acting as a ground cover, thus reducing evapotranspiration. whilst the maize offered a support structure for the beans to grow [7]. Furthermore, the mixed crop technique reduced the prevalence of pests and diseases, further minimizing the application of chemical pesticides due to the disruption of the pest cycle. This technique enhances pest management, thereby reducing the need for pest control and pest application, and invariably increases profitability [56].

Figure 12 shows how well the dataset is being trained using a correlation matrix.

Figure 13 presents the real-world data collected from farming activities and the linear regression model forecast estimating future crop yield profitability. The predicted total profitability is simply the sum of the individual crop profits, indicating that the actual and the predicted profits align in mixed crop scenarios, as shown below.

Particularly in affluent nations, solo crop systems have gradually supplanted mixed cropping. While mixed cropping has several benefits, including yield stabil-

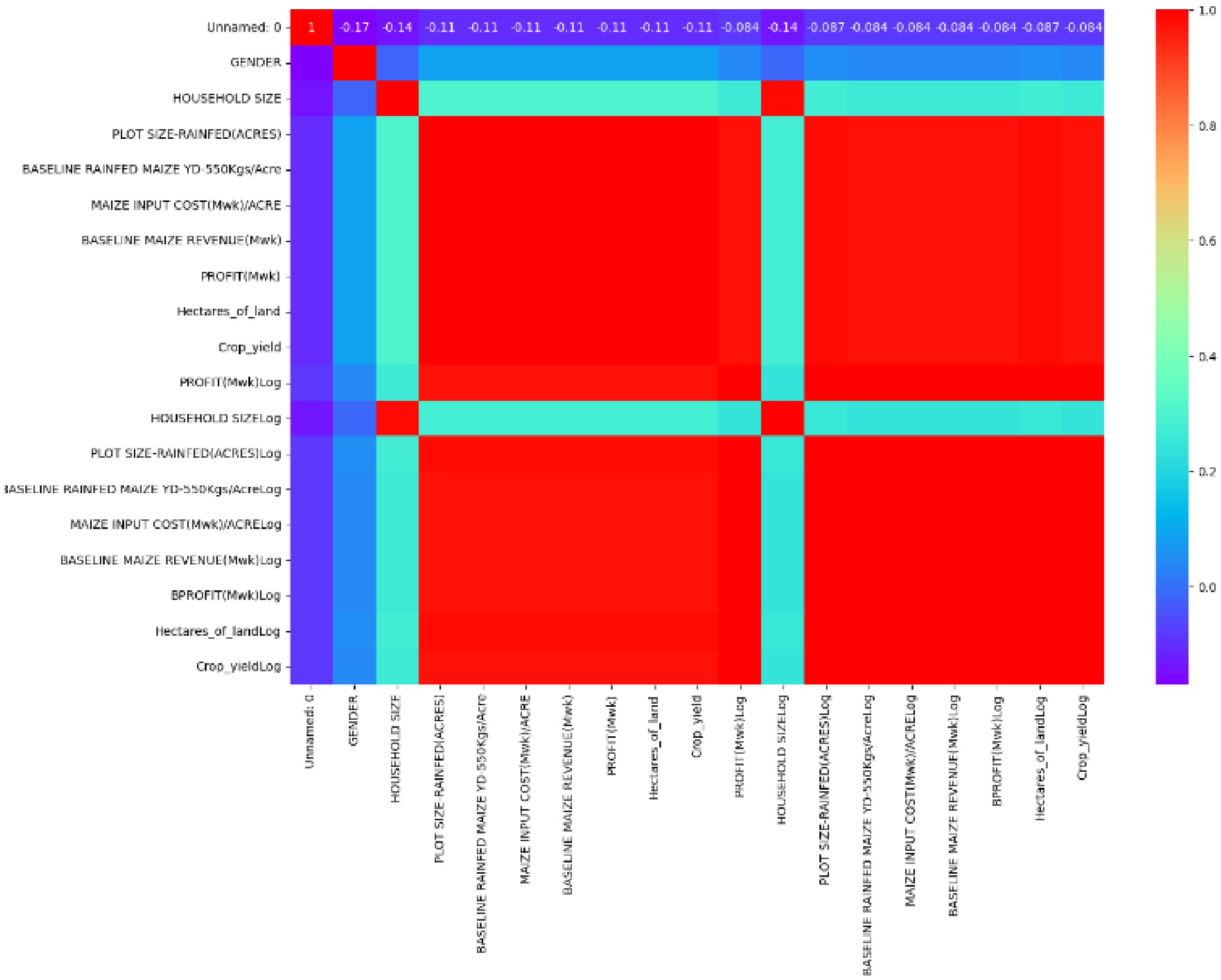

Figure 12. Correlation matrix as a heat map.

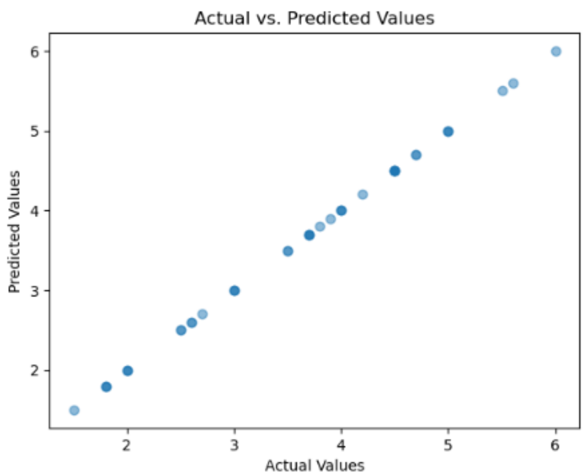

Figure 13. Visualization of actual value vs. predicted values of crop yield profitability.

ity and efficient use of resources, there are drawbacks, including competition and weed control. Mixed cropping techniques are beneficial for both profitability and sustainability in managing agricultural input and crop yield [57–59]. **Figure 14** compares the total profit for mixed crops against a single crop. Mixed crop (maize and beans) yield has the highest profitability at 46,234,500, while the maize sin-

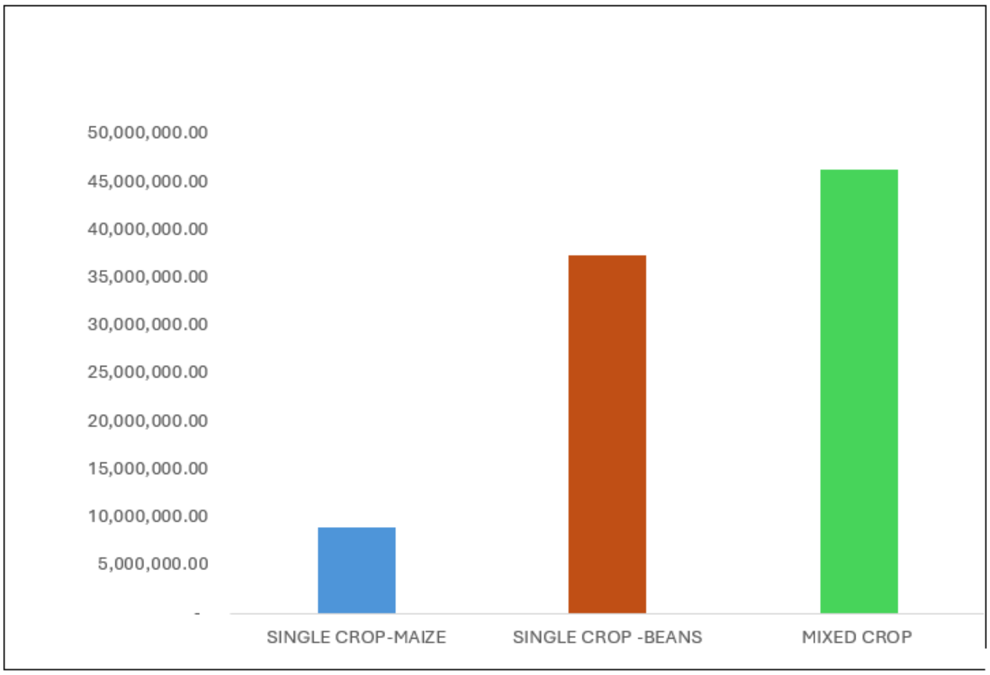

Figure 14. Profit comparison of mixed crop vs. single crop.

gle crop gave the least profitability value of 8,932,500, against the beans single crop profitability value of 37,302,000. Mixed cropping systems improve soil health through symbiotic relationships among crops. Adopting sustainable methods through mixed cropping will facilitate sustainable production, which will help to increase food security and alleviate poverty by enabling more resilient profitability and productive agricultural systems.

The results demonstrate that mixed cropping aligns more closely with sustainability than single cropping. Selecting complementary crops, managing soil health, using integrated pest management, and optimizing resource use will improve yields and profitability and will be environmentally sensitive. Therefore, sustainable agriculture has the potential to directly support several SDGs set forth by the United Nations for 2030, such as SDG 12 on responsible consumption and production, SDG 13 on Climate Action, and SDG 15 on life on land [60–67]. The practical and theoretical implications are evident in the results shown in **Figures 6–12**. Results showed that the dual crop yields of the two most grown crops, viz., maize and beans, were more profitable in comparison to both monocrop beans and maize plots. Male farmers had higher profits and yields than female farmers. These results show that sustainable and focused practices can be incorporated into farming systems and could ensure both profitability and sustainability.

5. Conclusion

The study outlined the challenges faced by SSF when balancing sustainability and productivity. The literature clearly shows that there is a trade-off between productivity and sustainability. SSFs are dependent on their operations for their livelihoods; thus, they are more inclined to choose practices that ensure a high monetary return. However, these kinds of practices are unable to compete when faced with adverse climatic occurrences. With growing populations that need to be fed, food insecurity that keeps rising, and climate change that disrupts and threatens agricultural production, it is in the best interest of policymakers to invest in educational programs and leverage technology adaptations for small-scale farmers. The policies drafted by countries to align with global climate change mitigation plans highlight agriculture as a key sector directly affected by climate change and should thus clearly outline easily implementable guidelines that farmers can adopt and offer incentives for their adoption. Further attention should be given to gender differences in productivity and profitability. Women farmers are more likely to adopt climate-smart agriculture; however, they need support structures in place to achieve this. Evidence shows that agroecological systems can deliver both profitability and sustainability. Practices such as intercropping with legumes in the case of maize, a staple in African countries, have enabled both profitability, good soil health, and fertility. Another leverage point is the use of precision agriculture, such as machine learning. Machine learning model assists in predicting yields as well as resource usage and disease prediction, which can save time and money for farmers. These results will help inform farmers and policymakers about high-risk prediction and daily decision-making for achieving sustainable agricultural development practices. Therefore, balancing profitability and sustainability in dual and mixed cropping involves integrating ecological principles with economic strategies and embracing SDGs 12, 13, and 15. With the adoption of innovative technologies, farmers can achieve a sustainable and profitable agricultural ecosystem. However, future research will be done using intensive multiple-cropping, environmentally friendly methods that focus on consistent yields over an extended period as more datasets are aggregated for comparison. Mixed cropping techniques are beneficial for both profitability and sustainability in managing agricultural inputs and crop yield.

6. Recommendation for future research

To further compare the Dowa and Lilongwe Central Districts. Multiple cropping systems exist to fit the context, wherein they are most beneficial. Agroecosystems are multifunctional and fare better against climate variables. Thus, a more methodical and quantitative evaluation needs to be introduced to include the beneficial environmental services that are part and parcel of these systems**.** Further analysis to demonstrate Machine Learning crop yield predictions using three-year data of farmers in Malawi, once the availability of more robust data is collated. Getting historical data will enhance accurate forecasting for crop profitability.

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Ethical consent to participate: We confirm that all methods were carried out in accordance with relevant guidelines and regulations. Informed consent was obtained from all subjects and/or their legal guardian(s).

Data availability: The datasets generated and/or analyzed during the current study are not publicly available because they involves data obtained from human participants. Mr. Chifuniro Kandaya should be contacted at Chifunirokandaya@yahoo.com or jaroba@uj.ac.za . for the dataset in this study. The link to the dataset https://data.mendeley.com/drafts/3smdsg355r Mendeley Data, V1, doi: 10.17632/3smdsg355r.1

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References

1. Mungai LM, Snapp S, Messina JP, et al. Smallholder farms and the potential for sustainable intensification. Frontiers Plant Science. 2016; 7: 1720. doi: 10.3389/fpls.2016.01720
2. Amede T, Konde AA, Muhinda JJ, et al. Sustainable farming in practice: Building resilient and profitable smallholder agricultural systems in Sub-Saharan Africa. Sustainability. 2023; 15: 5731. doi: 10.3390/ su15075731
3. Epule TE, Chehbouni A. The implications of agroecology and conventional agriculture for food security and the environment in Africa. In: Transitioning to Zero Hunger. MDPI; 2022. pp. 95–114. doi: 10.3390/books978-3-03897-863-3-4
4. Milheiras SG, Sallu SM, Loveridge R, et al. Agroecological practices increase farmers' well-being in an agricultural growth corridor in Tanzania. Agronomy for Sustainable Development. 2020; 42: 56. doi: 10.1007/s13593-022-00789-1
5. Cui Z, Zhang H, Chen, X. et al. Pursuing sustainable productivity with millions of smallholder farmers. Nature. 2018; 555: 363–366. doi: 10.1038/nature25785
6. Wittwer R, Bender A, Hartman SF, et al. Organic and conservation agriculture promote ecosystem multifunctionality. Science Advance. 2021; (7): eabg6995.
7. Ogosi OD, Begho T. Adoption of climate-smart agricultural practices in Sub-Saharan Africa: A review of the progress, barriers, gender differences and recommendations. Farming System. 2023; 1(2). doi: 10.1016/j.farsys.2023.100019
8. Willet W, Rockstrom J, Loken B, et al. Food in the Anthropocene: The EAT-Lancet commissions on healthy diets from sustainable food systems. The Lancet Commissions. 2019; 393: 447–492. doi: 10.1016/ S0140-6736 (18)31788-4
9. Streimikis J, Baležentis T. Agricultural sustainability assessment framework integrating sustainable development goals and interlinked priorities of environmental, climate and agriculture policies. Sustainable Development. 2020; 28(6): 1702–1712. doi: 10.1002/sd.2118
10. Seitz S, Goebes P, Puerta V, et al. Conservation tillage and organic farming reduce soil erosion. Agronomy for Sustainable Development. 2019; 39. doi: 10.1007/s13593-018-0545-z
11. Gram G, Roobroeck D, Pypers P, et al. Combining organic and mineral fertilizers as a climate-smart integrated soil fertility management practice in sub-Saharan Africa: A meta-analysis. PLoS One. 2020; 15(9). doi: 10.1371/journal.pone.0239552
12. Oliveira E, Wittwer M, Hartmann R, et al. Effects of conventional, organic and conservation agriculture on soil physical properties, root growth and microbial habitats in a long-term field experiment. Geoderma. 2024; 447: 116927. doi: 10.1016/j.geoderma.2024.116927
13. Adamtey M, Musyokab W, Zundel C, et al. Profitability and partial nutrient balance in maize-based conventional and organic farming systems in Kenya. Agriculture, Ecosystems and Environment. 2016; 235: 61–79. doi: 10.1016/j.agee.2016.10.00113
14. Murendo C, Kairezi G, Mazvimavi K. Resilience capacities and household nutrition in the presence of shocks. Evidence from Malawi. World Development Perspectives. 2020; 20: 100241. doi: 10.1016/j.wdp.2020.100241
15. Cairns JE, Chamberlin J, Rutsaert P, et al. Challenges for sustainable maize production of smallholder farmers in sub-Saharan Africa. Journal of Cereal Science. 2021; 101: 103274. doi: 10.1016/j.jcs.2021.103274
16. FAO. The Status of Women in Agrifood Systems. Rome; 2023.
17. Nkomoki W, Bavorová M, Banout J. Factors associated with household food security in Zambia. Sustainability. 2019; 11: 2715. doi: 10.3390/su11092715
18. Pawlak K, Kołodziejczak M. The role of agriculture in ensuring food security in developing countries: Considerations in the context of the problem of sustainable food production. Sustainability. 2020; 12(13): 5488. doi: 10.3390/su12135488
19. Mbuli CS, Fonjong LN, Fletcher AJ. Climate change and small farmers' vulnerability to food insecurity in cameroon. Sustainability. 2021; 13: 1523. doi: 10.3390/su13031523
20. Cousins B. Small-scale farmers should be at the centre of land reform in South Africa. 2018. Available online: https://theconversation.com/small-scale-farmers-should-be-at-the-centre-ofland-reform-in-south-africa-94546 (accessed on 23 October 2025).

21. Dhillon R, Moncur Q. Small-scale farming: A review of challenges and potential opportunities offered by technological advancements. Sustainability. 2023; 15(21): 15478. doi: 10.3390/su152115478
22. Aroba OJ, Rudolph M. Systematic literature review on the application of precision agriculture using artificial intelligence by small-scale farmers in Africa and its societal impact. Journal of Infrastructure, Policy and Development. 2024; 8(13): 8872. doi: 10.24294/jipd8872
23. Rockström J, Williams J, Daily G, et al. Sustainable intensification of agriculture for human prosperity and global sustainability. Ambio. 2017; 46(1): 4–17. doi: 10.1007/s13280-016-0793-6
24. Kennedy E, Jafari A, Stamoulis KG, et al. The first programmes food and nutrition security, impact, resilience, sustainability, and transformation: Review and future directions. Global Food Security. 2020; 26: 100422. doi: 10.1016/j.gfs.2020.100422
25. Jones K, Nowak A, Berglund E, et al. Evidence supports the potential for climate-smart agriculture in Tanzania. Global Food Security. 2023; 36. doi: 10.1016/j.gfs.2022.100666
26. National Climate Change Management Policy (NCCMP). Government of Malawi. Ministry of Natural Resources Environment and Mining. Environmental Affairs Department; 2016.
27. Tufa AH, Arega AD, Cole SM, et al. Gebder differences in technology adoption and agricultural productivity: Evidence from Malawi. World Development. 2022; 159. doi: 10.1016/j.worlddev.2022.106027
28. Anderson LC, Reynolds TW, Biscaye P, et al. Economic benefits of empowering women in agriculture: Assumptions and evidence. The Journal of Development Studies. 2020; 57(2). doi: 10.1080/00220388.2020.1769071
29. Phiri A, Chipeta GT, Chawinga WG. Information needs and barriers of rural smallholder farmers in developing countries: A case study of rural smallholder farmers in Malawi. Information Development. 2018; 35(3): 421–434. doi: 10.1177/0266666918755222
30. Kamanga BC, Kanyama-Phiri GY, Waddington SR, et al. The evaluation and adoption of annual legumes by smallholder maize farmers for soil fertility maintenance and food diversity in central Malawi. Food Security. 2014; 6: 45–59. doi: 10.1007/s12571-013-0315-3
31. Mango N, Makate C, Mapemba L, et al. The role of crop diversification in improving household food security in Central Malawi. Agriculture and Food Security. 2018; 7: 160. doi: 10.1186/s40066-018-0160-x
32. McLaughlin SM, Bozzola M, Nugent AN. Changing climate, changing food consumption? Impact of weather shocks on nutrition in malawi. The Journal of Development Studies. 2023; 59(12): 1827–1848.
33. Valeriano D. Assessing water balance and yields in malawian cropping systems: Maize soybean and maize Gliricidia systems resilience against climate change. Second cycle, A2E. Uppsala: SLU, Departmwent of Soil and Environment; 2024.
34. FAO. Status of the world's soil resources: Technical summary. Rome, Italy; 2018. pp. 1–94.
35. Tahat MM, Alananbeh MK, Othman AY, et al. Soil health and sustainable agriculture. Sustainability. 2020; 12(12): 4859. doi: 10.3390/su12124859
36. Davis AG, Huggins DR, Reganold JP. Linking soil health and ecological resilience to achieve agricultural sustainability. Frontiers of Ecology and the Environment. 2023; 21(3). doi: 10.1002/fee.2594
37. Altieri MA, Nichols CI, Henao A, et al. Agroecology and the design of climate change-resilient farming systems. Agronomy for Sustainable Development. 2015; 35(3): 869–890. doi: 10.1007/s13593-015-0285-2
38. Elbasi E, Zaki C, Topcu AE, et al. Crop prediction model using machine learning algorithms. Applied Sciences. 2023; 13: 9288. doi: 10.3390/app1316928
39. Khaki S, Wang L. Crop yield prediction using deep neural networks. Frontiers in Plant Science. 2019; 10: 621. doi: 10.3389/fpls.2019.00621
40. González SA, Frausto SJ, Ojeda BW. Predictive ability of machine learning methods for massive crop yield prediction. Spanish Journal of Agricultural Research. 2014; 12(2): 313–328. doi: 10.5424/sjar/2014122-4439
41. Adeleke O, Aroba OJ, Adebayo S, et al. Impact of a workplace screening programme for hypertension: A 5-year machine learning-based analysis of a university workforce medical records. Preprint. 2023; 1–15. Available online: https://www.preprints.org/manuscript/202405.1861 (accessed on 23 October 2025).
42. Pant J, Pant RP, Singh M, et al. Analysis of agricultural crop yield prediction using statistical techniques of machine learning. Materials Today: Proceedings. 2021; 46: 10922–10926. doi: 10.1016/j.matpr.2021.01.948
43. Filippi P, Jones EJ, Wimalathunge NS, et al. An approach to forecast grain crop yield using multi-layered, multi-farm data sets and machine learning. Precision Agriculture. 2019; 1–15. doi: 10.1007/s11119-018-09628-4

44. Aroba OJ, Rudolph M. Smart technologies system implementation using a case study in the south african library education sector. In: International Conference on Innovations in Bio-Inspired Computing and Applications; 2025. pp. 465–478. doi: 10.1007/978-3-031-78949-6_51
45. Ngwira AR, Kabambe V, Simwaka P, et al. Productivity and profitability of maize-legume cropping systems under conservation agriculture among smallholder farmers in Malawi. Acta Agriculturae Scandinavica, Section B—Soil & Plant Science. 2020; 70(3): 241–251. doi: 10.1080/09064710.2020.1712470
46. Droppelmann KJ, Snapp SS, Waddington SW. Sustainable intensification options for smallholder maize-based farming systems in Sub-Saharan Africa. Food Security; 2016. doi: 10.1007/s12571-016-0636-0
47. Alvarez R. Comparing productivity of organic and conventional farming systems: A quantitative review. Archives of Agronomy and Soil Science. 2021; 68(14): 1947–1958. doi: 10.1080/03650340.2021.1946040
48. White M, Heros E, Graterol E, et al. Balancing economic and environmental performance for small-scale rice farmers in Peru. Frontiers in Sustainability Food Systems. 2020; 4: 564418. doi: 10.3389/fsufs.2020.564418
49. Muraina IO. Ideal dataset splitting ratios in machine learning algorithms: General concerns for data scientists and data analysts. In: 7th International Mardin Artuklu Scientific Research Conference; 2022. pp. 496–504.
50. Wang S, Xiong J, Yang B, et al. Diversified crop rotations reduce groundwater use and enhance system resilience. Agricultural Water Management. 2023; 276. doi: 10.1016/j.agwat.2022.108067
51. Chipeta MM, Kampanje-Phiri J, Moyo D, et al. Understanding specific gender dynamics in the cowpea value chain for key traits to inform cowpea breeding programs in Malawi, Mozambique and Tanzania. Frontiers in Sociology. 2024; 9: 1254292.
52. IFPRI. The impact of gender on agricultural productivity in Malawi. International Food Policy Research Institute; 2018.
53. MoAIWD. Malawi Agriculture Sector Performance Report. Ministry of Agriculture, Irrigation, and Water Development; 2019.
54. WLA. Women's Land Rights in Malawi. Women's Land Arms; 2020.
55. Taylor A, Wynants M, Munishi L, et al. Building climate change adaptation and resilience through soil organic carbon restoration in Sub-Saharan rural communities: Challenges and opportunities. Sustainability. 2021; 13(19): 10966. doi: 10.3390/su131910966
56. Antwi-Agyei P, Abalo E, Dougill M, et al. Motivations, enablers and barriers to the adoption of climate-smart agricultural practices by smallholder farmers: Evidence from the transitional and savannah agroecological zones of Ghana. Regulation (on) Sustainability. 2021; 2(4): 375–386. doi: 10.1016/j.regsus.2022.01.005
57. Sneessens I, Veysset P, Benoit, et al. Direct and indirect impacts of crop–livestock organization on mixed crop–livestock systems sustainability: A model-based study. Animal. 2016; 10(11): 1911–1922.
58. Issahaku G, Abdulai A. Adoption of climate-smart practices and its impact on farm performance and risk exposure among smallholder farmers in Ghana. Australian Journal of Agricultural Resource Economics. 2020; 64(2): 396–420. doi: 10.1111/1467-8489.12357
59. Alam S, Krupnik TJ, Sharmin S, et al. Alternative cropping and feeding options to enhance sustainability of mixed crop-livestock farms in Bangladesh. NJAS: Impact in Agricultural and Life Sciences. 2024; 96(1): 2290046.
60. Piñeiro V, Arias J, Dürr J, et al. A scoping review on incentives for adoption of sustainable agricultural practices and their outcomes. Nature Sustainability. 2020; 3(10): 809–820.
61. Ugbedeojo M, Adebiyi MO, Aroba OJ, et al. RSA and Elliptic curve encryption system: A systematic literature review. International Journal of Information Security and Privacy (IJISP). 2024; 18(1): 1–27. doi: 10.4018/IJISP.340728
62. Aroba OJ. The implementation of augmented reality in internet of things for virtual learning in higher education. International Journal of Computing Sciences Research. 2024; 8: 2536–2549. doi: 10.25147/ijcsr.2017.001.1.174
63. Aroba OJ. Professional leadership investigation in big data and computer-mediated communication in relation to the 11th Sustainable Development Goals (SDG) Global Blueprint global blueprint. International Journal of Computing Sciences Research. 2024; 8(2024). doi: 10.25147/ijcsr.2017.001.1.177
64. Adebayo S, Aworinde HO, Olufemi OO, et al. Understanding mushroom farm environment using TinyML-based monitoring devices. Environmental Research Communications. 2025; 7(4): 045014. doi: 10.1088/2515-7620/adc5cd
65. Aroba OJ, Rudolph M. An ERP implementation case study in the BRICs country south african BRICS south africa economic tourism economic sector. International Journal of Computer Information Systems and Industrial Management Applications. 2025; 17: 11. doi: 10.70917/ijcisim-2025-0005

66. Aroba OJ, Xulu T, Msani NN, et al. The adoption of an intelligent waste collection system in a smart city. In: 2023 Conference on Information Communications Technology and Society (ICTAS); 8-9 March 2023; Durban, South Africa. IEEE; 2023. pp. 1–6. doi: 10.1109/ICTAS56421.2023.10082750
67. Aroba OJ, Owoputi AO, Fagbola TM. An SAP enterprise resource planning implementation using a case study of hospital management system for inclusion of digital transformation. International Journal of Computer Information Systems and Industrial Management Applications. 2023; 15: 12.