Volume 1, 2025, Pages 196-205 *Journal of Smart and Sustainable Farming*
| Regular Article | Open Access

Climate Smart Maize in Sub Saharan Africa: An Integrated Evaluation Using Agro Technologies and Climate Projections

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Article Info
Journal of Smart and Sustainable Farming
https://www.ansispublications.com/journals/jssf/jssf.html

Received 30 July 2025
Revised from 31 August 2025
Accepted 25 October 2025
Available online 02 November 2025
Published by Ansis Publications.

https://doi.org/10.64026/JSSF/2025019

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Abstract – This paper evaluates the effects of the climate smart agriculture (CSA) practice through scenario-based modelling, in 3 climate change vulnerable SSA (sub) regions (Malawi, Tanzania, and Zambia). Effects of two Agri techno pathways, including Low Tech (LT) and High Tech (HT) on the intensity of greenhouse gases emissions, water productivity and maize yield were contrasted and identified under two climate scenarios (RCP2.6 and RCP 8.5). To aid in cross-scenario and cross-country comparison, a climate smartness index (CSI) was created, which included productivity, resource use efficiencies, mitigation and resource use efficiencies. Findings show that HT futures have significant CSI value improvements, with the majority of these improvements being in the areas of yield increase, water-use efficiency, and unit grain emissions. Irrigation and uptake of better maize varieties also mitigate the yield shock and this shows the importance of interventions through technology in ensuring that agricultural systems are developed in a manner that is climate-resilient.

Keywords – Climate-Smart Agriculture, Maize Productivity, Sub-Saharan Africa, Agro -Technological Development, Climate Smartness Index, Water Productivity, Greenhouse Gas Emissions.

I. INTRODUCTION

Maize is cultivated on over 100 million hectares in poor nations, with almost 70% of global maize output originating from low and lower-middle-income countries. By 2050, the demand for maize in the developing world is expected to double, and it is projected to become the most produced crop worldwide, as well as in the developing world, by 2025. In extensive regions of Africa, maize serves as the primary staple grain, constituting an average of 32% of caloric intake in Eastern and Southern Africa, with figures escalating to 51% in some nations.

Climate change is characterized by substantial long-term changes in meteorological conditions, including precipitation and temperature. The effects of climate change are unavoidable and experienced worldwide. The influence of climatic variables on productivity in agriculture continues to be an issue of concern and, in the face of rising agricultural demands, an issue of greater concern. Specifically, to meet the food demands of a world population of 9 billion by 2050, a 70\% increase in the production of staple grains will be required.

The promotion and dissemination of technology are important in the agricultural sector. Traditional agricultural extension services offer in-person, on-site assistance and direct contact with farmers, which means that agricultural specialists and other staff need to be physically present. These services are constrained by time and space, needing to be scheduled around trips to remote rural and hilly areas, and in this case an agricultural extension service. This innovative agribusiness service model greatly changes the dissemination and commercialization of agrotechnology. This model combines information and technology to give farmers customized services.

The continuing advancement and improvement of new technologies will certainly affect the productivity and the sustainability of the agricultural sector. Farmers, and other participants in the food production system, will be provided with information and tools that are expected to enhance their decision-making ability. The introduction of smart farming techniques including precision farming as well as advanced analysis of data in order to make better decision, to use resource efficiently, and to increase productivity of agriculture. Availability of real time data on soil, weather, and growth of crops allow farmers to take better decisions, and therefore increase efficiency and decrease inefficiencies.

The recent advancements in agriculture technology and its dissemination impacts positively on the 475 million small farms worldwide. Small farms constitute a significant portion of the agriculture sector worldwide and therefore they stand to benefit immensely from new technology. Affordable sensors, applications, and robotics can help small farmers to increase efficiency in farm operations which will lead to higher profitability. Technology can offer market information, supply chain management and integration into the international market for small farmers.

Climate-Smart Agriculture (CSA) is identified as the foundation for dramatic advancements in sustainability. In response to climate challenges, CSA, founded on the pillars of mitigation, adaptation, and productivity, has been proposed as an agricultural approach designed to concurrently achieve three objectives: enhancing productivity, adapting to global warming, and diminishing greenhouse gas (GHG) emissions. For significance, these general CSA aims must be converted into particular characteristics of agricultural models, tailored to the essential temporal and geographical dimensions and agro-climatic environments of those models.

In some agricultural systems, it is infeasible to concurrently maximize all three of these overarching goals. The intricate trade-offs and compatibilities among production, adaptation, and mitigation, goals have led to difficulties in the interpretation of the CSA concept within agricultural planning, and policy. It remains ambiguous whether a yield-optimizing approach is more or less climate-intelligent than one focused on justification, or one that seeks a balance between the two. It should be noted that climate intelligence or smartness is a relative concept thereby adding to its ambiguity.

Maize systems in Sub-Saharan Africa (SSA) are very susceptible to climate changes and also experience a sustained yield gap because of low technology development. The concept of the ability of integrated agro-technological interventions to improve productivity, water-use efficiency and reduction of emissions is the key element in designing sustainable and resilient models of food. The paper presents a quantitative model that can be used to determine and evaluate the interaction of technology and climate on maize systems, investment choices and viable policy to meet climate-smart agriculture in the region.

The rest of the paper is structured accordingly: Section II describes previous literature works on CSI and other agro-technologies. Section III describes the study area, data sources, and model frameworks. Section IV is a discussion of our findings, which provides an understanding of CSI under baseline and futuristic cases, and maize yield/productivity shocks, as well as the role of improved/irrigated varieties. Lastly, Section V concludes our study showing that the greater the level of agro-technology being implemented, the most positive climate-smart outcomes are attained across the maize systems of the three SSA countries.

II. LITERATURE REVIEW

Kabato et al. [1] examine climate-smart Agriculture (CSA), food security, and agricultural yields relationship. The irregularities in rainfall such as deficits and excesses have been diagnosed to be a contributor to negative impacts on agricultural production in various smallholder settings. CSA strategies such as increased crop diversities have been developed and disseminated in response to the long dry seasons in various arid/semi-arid areas of the African continent. Such improved climate-resistant crop diversities are tolerant to heat stress and drought, and it is possible that more crop yields can be produced by various production systems. Besides these improved types of crops, other climate-resistant methods are cereal-groundnut intercropping (growing groundnuts in addition to sorghum, millet, or maize) and the use of organic fertilizers (composts, farm and animal manure).

According to Dhillon and Moncur [2], CSA is built on the basis of set guidelines, technology, and knowledge of sustainable increase, requiring the awareness of the importance of cultural environment and local models of indigenous knowledge. While akin to other agronomic methods, CSA distinctly prioritizes their application, emphasizing flexibility, contextual relevance, and the need of climate funding to address the investment shortfall in climate change adaptation. Crucially, CSA emphasizes climate change and evaluates the trade-offs and synergies of agricultural production, climate change mitigation, and climate change adaptation.

According to Kabato et al. [3], yield/production gaps refer to the difference between real crop yields in a certain site and the yields that might be achieved with the use of more timely and optimum inputs, cultivars, and management practices. Production levels in most of the Global North have plateaued at their top limits, whilst significant yield disparities persist in the Global South. The presence of substantial production gaps between actual and potential yields indicates more possibilities and chances for production enhancement. A refined comprehension of production gaps and the many reasons that impede agriculturalists from enhancing productivity and production may facilitate the identification of possibilities for sustainable intensification of agriculture. This information and insights may also facilitate pertinent policies for agricultural growth in SSA.

Prior efforts to assess yield gaps in SSA are typically grounded on agronomic study using main data gathering from official yield or farmers' fields statistics to assess real output, alongside measured farm experiments or/and crop modeling to predict (water-less) prospective production. The choice and integration of the aforementioned approaches are contingent upon context and eventually influence the ambiguity of the production gap approximation. Official crop production estimates derived from agriculturalists' self-reported data are recognized for their significant uncertainty; however, they are reasonably cost-effective to gather. Conversely, primary data collection could yield greater accuracy but it can be rather resource-consuming especially in situations where a large area is being investigated.

According to Zhu et al. [4], crop simulation models are an extremely significant development in the understanding and predicting agro-ecosystem productivity, however, their use is limited by the fact that data and expertise are required to validate, calibrate and parameterize the model before it can be implemented with much certainty. The calibration of the models and testing of all new crop environments and varieties are an absolute necessity, but the implementation of this scenario on a practical level might not be possible due to the lack of architecture and human/financial resources needed to collect all the data on the growth and phenological assessment.

Crop models under the SSA context form a major basis of uncertainty because they are mostly validated and calibrated using information collected off SSA and hence they include a combination of different types of crop varieties and ecological environments which are not necessarily relevant in the SSA environment. Malawi has seen many food crises, and the population facing extreme food insecurity is consistently rising. The current average maize product is approximately 2 t/ha, which is much lower than its potential. Depletion of cultivated soils has occurred due to heightened land demand and inadequate inputs. Farmers have used cropland expansion at the cost of forests as a tactic to enhance production by cultivating more fertile soils.

Ahmed et al. [5] assessed the yield gaps and potential yields of NCP summer maize, with disparate finding. They calculated that the average possible production of maize, based on MCWLA-Maize simulations and nation-based statistical dataset from 1980 to 2008, ranged from 7.0 to 11.0 t ha^{-1}, with gap being approximately 40% to 60% of the possible NCP yield. They calculated that the average potential yield was approximately 10 to 30% lower, from 9.71 to 12.92 t ha^{-1}, with the gap constituting 40.51%–72.42% of the potential production, based on data from 10 locations using APSIM-maize framework (record timeframe from 1981 to 2009).

Recent research by Qiao et al. [6] employed a Hybrid-Maize framework according to the procedures of the Global Yield Gaps Atlas, and calculated the average potential maize yield in NCP to be 11.91 t ha^{-1} (from 2006 to 2012), with the farm-level production gap ranging from 30.3% to 48.7%. They estimated that the mean gap of maize within NCP was 10.31 t ha^{-1} from 1990 to 2009.

In contrast, Gao et al. [7] documented a much-reduced gap of just 2.32 t ha−1 for the period of 2005 to 2007 in the Hebei-Tianjin-Beijing area of northern NCP. These research works enhanced the comprehension of maize yield gaps in the NCP, although seldom integrated recent fluctuations in maize production (post-2010), a period during which maize production experienced significant stagnation in the NCP. Furthermore, they failed to consider the potential enhancement of maize output or the optimal places for its improvement. Consequently, we evaluated the prospective yields and production gap of summer maize at the national level, using the most recent data to comprehend the possible enhancement of maize output and to provide farming policy recommendations.

Davis [8] define technology as the means and procedures used in the production of services and products, including organizational approaches and physical approaches. These writers assert that new technology is either unfamiliar to a certain location or set of farmers, or signifies a novel use of existing technology within that locale or among that population. Technology encompasses the knowledge and information that facilitates the execution of activities, the provision of services, or the production of goods. Technology is designed to enhance a certain situation or transform the status quo into a more favorable condition. It facilitates the applicant's job more efficiently than without the technology, so conserving time and labor. Conversely, adoption is defined in many ways by different writers.

Khanagha et al. [9] defines adoption as the incorporation of a novel technology into established practices, often preceded by a phase of experimentation and a certain level of modification. They characterized adoption as a cognitive process that a person undergoes from first awareness of an invention to its ultimate use. Adoption is categorized into two types: rate of adoption and intensity of adoption. Former is a relative speed at which agriculturalists adopt an invention, where time is one of its basic points. The adoption level refers to how much a particular technology is applied in a specified period.

Such a definition of technology adoption is not an easy task because it varies according to the type of technology that is adopted. According to the research by Hamadziripi et al. [10], CIMMYT considered farmers as adopters when they used seeds which were later recycled more than two times on the hybrid progenitors. They noted that adoption related to compliance with the extension service recommendation on the use of new certified seed only. When defining agricultural technology adoption by farmers, the initial aspect to look at is whether adoption is an observable status whereby the response variables are binary in nature. The definition would depend on the status of the farmer as an adopter or non-adopter of the technology would be represented by a zero and a one value or whether a continuous variable is the answer.

This method, though essential, is not enough as a dichotomy answer signifies being aware of improved technology but not using it in reality, as stated by Edmondson et al. [11]. It follows that the phrase technology adoption should be clearly defined by the researchers in order to be able to create adequate measurement tools. Despite the potential benefits of agricultural technology, the adoption of agricultural technology is slow in smallholder farmers (who make up more than eighty percent of the world farming population). Such farmers may not be able to have access to the resources, money, and facilities to implement modern equipment.

According to a survey conducted by Ngulube [12], out of the 1.1 billion smallholder farmers in the world only under 20 percent employ advanced technology such as the Internet of Things (IoT) or satellite technology. Such aspects as high upfront costs, lack of confidence in technology, and lack of digital literacy are some of the reasons that limit the adoption of Agri-Tech among a large number of farmers. many farmers struggle to access reliable advisory services to understand how these technologies can be used to address their specific needs. The lack of this adoption denies the smallholders the economic benefits of increased production and efficiency.

Feder, Just and Zilberman [13] state that the level of adoption of agricultural technologies in industrialized and developing countries vary significantly. Big farms in developed countries have implemented AI-based analytics and autonomous technology, whereas the small holders in low-income countries usually rely on traditional methods of farming. Precision agricultural technology is applied on over 60 percent of large-scale farms in Europe and North America and under 10 percent in SSA and parts of South Asia. The disparity is caused by factors such as lack of adequate infrastructure as well as a limited access to finances and government support in the third world countries. It is important to bridge this technological gap in order to have a fair agricultural progress and address the global food security challenges.

III. MATERIALS AND METHODS

Study Area and Data Sources

The research centers on Malawi, Zambia, and Tanzania which are all SSA countries with climate sensitive maize production systems (see **Fig. 1**). All these countries hold agricultural importance and are climate sensitive maize production systems. These countries are also heterogeneous in their biophysical characteristics such as their rainfall patterns, temperatures, soil fertility, and irrigation potential. Malawi is characterized by high interannual variability in unimodal rainfall, Tanzania is comprised of multiple agroecological zones with varied climactic gradients, and Zambia has large areas of cultivable land although irrigation is not well developed. Collectively, these countries are climate smart agricultural futures geographically relevant.

Baseline datasets were pulled together from different national and international datasets. For historical climate data (1990-2010), we gathered from gridded observational datasets that provided daily precipitation amounts, daily minimum and maximum temperatures, and daily potential evapotranspiration. Also included were soil profile data from harmonized soil data that described root depth, available water capacity, texture, organic matter content, and soil water evaporation. Crop management baselines were developed from national agricultural surveys that described current levels of fertilizer use, adoption of improved maize varieties, planting density, and tillage practices. To assess agricultural water availability, we used cropland extent and land use and irrigation system coverage datasets. We used country level agricultural production data to validate baseline yield distributions and determine historical yield shocks.

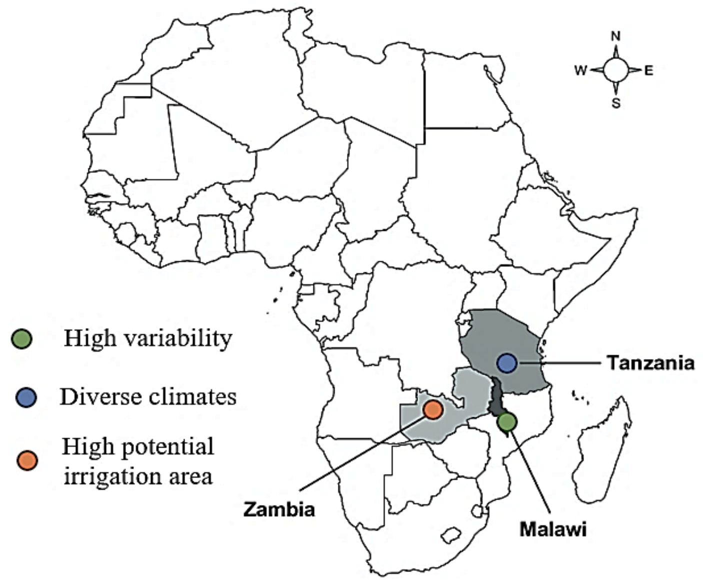

Fig 1. Conceptual Study Area Map.

Scenario and Model Framework

The combined effects of agro technology advancement and climate change on maize productivity, water utilization, and greenhouse gas emission, were evaluated using scenario-based modeling approach. Two scenarios of agro technology were defined as depicted in **Fig. 2**.

LT Scenario

This describes the perpetuation of existing farming systems which are low in fertilizer application, do not use better seed varietals, are rain fed and agronomic systems are the same. This scenario depicts a serious technological stagnation, which is commonly perceived in smallholder farming mechanisms in SSA.

HT Scenario

This portrays an optimistic and feasible future with an improved agricultural tech ecosystem. This comprises more drought tolerant maize varieties, precision application of fertilizers, more mechanized farms, better extended support, and improved irrigation. Technological advancement in the HT scenario is guided more by realism than by ambition. For climate projections, an ensemble of climate models and two Representative Concentration Pathways were used: RCP2.6 (low) and RCP8.5 (high). For the mid-century (2050-2060), climate projections were downscaled and used in the iFEED modeling platform to produce estimations of crop yields, water use and GHG emissions.

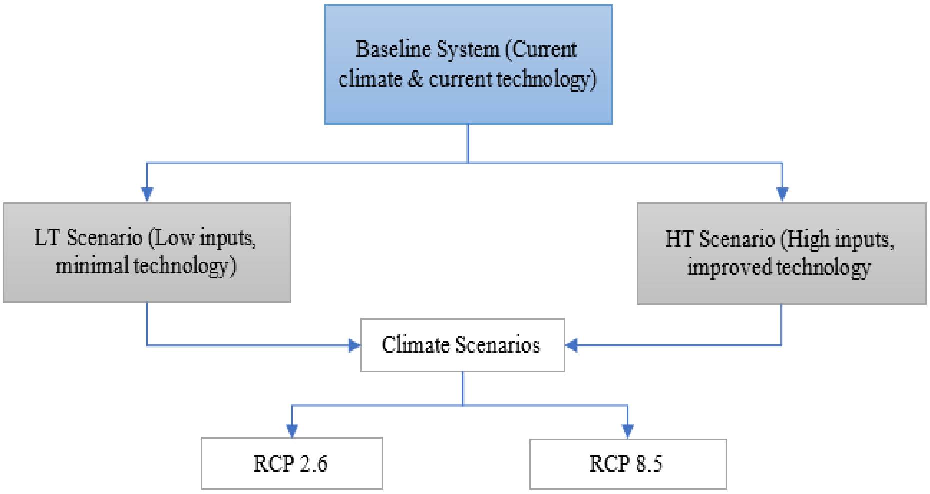

Fig 2. Scenario Structure.

It has been established that yield shock thresholds are historical baseline yields that are more than one standard deviation from the long-term mean. To quantify the number of simulations with extreme yield low years, these thresholds were calculated.

Computation of Indicators
To evaluate the outcomes of climate-smart agriculture in the different scenarios, we computed the following performance indicators: Climate Smartness Index (CSI), Water Productivity (WP), and Greenhouse Gas Emission Intensity (GHGI).

CSI
CSI quantifies the degree of gain in productivity, improvement in GHG emission intensity, improvement in water productivity, and the gain level of each dimension against the baseline. To allow for multidimensional space comparisons, the index was standardized. Areas with positive index values are considered climate smart, i.e., their agriculture produces more with shared losses of emission, emission intensity, and water use in the future. The CSI was constructed to achieve the integral measurement of the performance of the agricultural system with respect to walking the combined technological and climate pathways. The index measures the extent to which yield, water productivity, and GHG emission intensity change in the positive direction at the same time for more climate-wise outcomes, in a multi-step consistent and robust methodological system to achieve outcomes of climate smart agriculture.

Conceptualization of the CSI Components
The CSI is based on the three central pillars of the CSA, which is the increased productivity, enhanced resource-use efficiency, and reduced emissions intensity. Of these, WP is wheat productivity. GHGI is the greenhouse gas emission intensity and is the mitigation pillar. Even though these indicators differ, each one alone is insufficient to characterize climate smartness. This is due to the fact that an advancement in one field might happen simultaneously with regression in another. The composite index thus facilitates the concurrent assessment of multidimensional performance, capturing synergies and trade-offs.

Standardization and Directional Transformation
Given that there were differences in the units, sizes, and directions of the indicators, the first step was to equalize the benchmark means of each different metric. Each of the countries base period (1990-2010) was treated as the reference state. Each of the indicators was converted to a standardized score through a process of z-score normalization. The standardized form of a generic indicator X, was calculated using Eq. (1).

$$Z_X = \frac{X_{sc} - \mu_{X,base}}{\sigma_{X,base}} \quad (1)$$

where X_{sc} is the simulated value based on the given scenario-climate combination, $\mu_{(X,\text{base})}$, is the mean of the baseline value, and $\sigma_{(X,\text{base})}$ is the baseline value of the standard deviation, the standardized index measures the simulation value's distance from the recorded simulation value and paves the way for comparison across divergent scenarios.

This transformation enabled all indicators to be presented on a dimensionless scale that is standard, thus removing the bias created by different scales of measurements. Some directional consistency was guaranteed before aggregation. Because an increase in the value of the GHGI is an indication of an increase in the deterioration of the environmental performance, standardized values of the GHGI were multiplied by -1, thus correcting the direction to the positive of the climate smartness. Therefore, more climate-smart outcomes are enabled by higher values of all standardized scores.

Mathematically, the directional correction is expressed using Eq. (2).

$$Z_{GHGI}^{\backslash *} = -Z_{GHGI} \tag{2}$$

where $Z_{GHGI}^{\backslash *}$is the adjusted term included in CSI computation.

Aggregation Framework and Weighting Logic

Subsequent to the recalibration and standardization process, the three components were combined to form the composite CSI. Methodologically, all three pillars were assigned equal weights to avoid bias toward the pillar of productivity, water use, or emissions. Equal weighting corresponds to the conceptual basis of CSA, whereby productivity, adaptation, and mitigation are seen as equally important for climate-smart performance.

The CSI for each simulation was calculated using Eq. (3).

$$CSI = \frac{1}{3}(Z_{Yield} + Z_{WP} + Z_{GHGI}^{\backslash *} \tag{3}$$

This methodology permits a visible and comprehensible design of the index. Because of its additive linear aggregate method, one can examine and evaluate the index components separately and simultaneously.

Inter-Scenario Comparability

Since each baseline was country-specific, metrics standardized, making CSI scores comparable, regardless of scenario, technology, or climate pathway. Climate smartness baseline, minus value, worse than baseline, is geographically worse, and plus value, is better, climate smart CSA. Because of this standardization, the study was able to analyze the cross-country differences without absolute yield or emission differences.

Sensitivity Checks and Robustness Considerations

To verify that no extreme single-parameter fluctuations were affecting CSI values, sensitivity checks were conducted by CSI recalculating using different weighting schemes i.e. productivity-weighted and mitigation-weighted. These checks reflected that CSI position across scenarios were still stable, thereby confirming robustness of the equal-weighting approach. This also provided assurance that the composite indicator captured truly reflected the overall climate smartness rather than any single extreme.

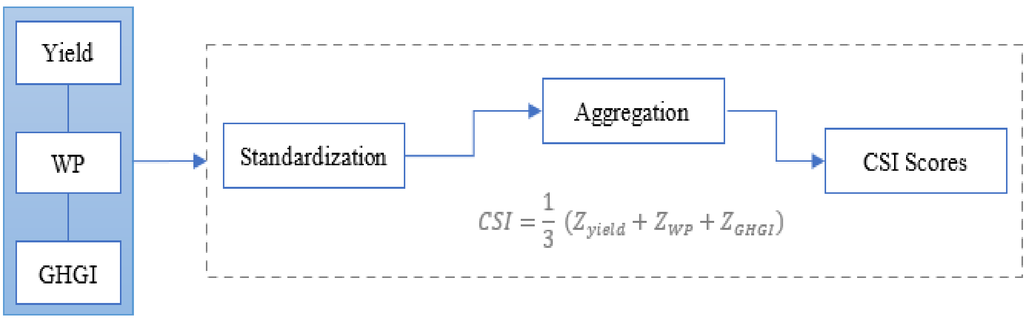

Fig 3. CSI Development and Calculation Process.

Interpretation of CSI Values in Model Outputs

There is a positive correlation between the adoption of the technology, productivity gains, and the use of water along emissions and the decreasing of intensity of emissions. The positive CSI values for HT scenarios represent the potential of the synergies across the metrics to flow from the further amplified productivity to enhanced resource use. On the other side of the spectrum, the CSI values for LT or baseline conditions represent the inefficiencies in low input systems in terms of productivity, the use of fertilizer is low, the rainfall is erratic, and yet there is a GHG intensity which is comparatively high, which is the norm for such systems.

Fig. 3 summarizes the flow of the 4-step process undertaken during the development of the composite indicator of census. The first part shows the indicator obtained from standardization of the yield, WP, and GHGI. The second part shows the directional transformation and then standardization. The third part illustrates out the weighting and the aggregation which results in the final composite score of the CSI. The fourth part shows the output from the CSI score being projected in various countries, and across different scenarios in climate pathways.

Water Productivity

Crop water productivity (CWP) is an essential statistic for evaluating agricultural water use and efficiency. It is defined as the crop productivity ratio in comparison to water volume used in its production. The water footprint (WF) of a crop is a standard measure for evaluating agricultural water use and efficiency. We use remote sensing technologies to update and improve the methodology of current WF datasets. CWP can be used as an objective and practical measure of efficiency of agricultural water use.

Remote sensing technology offers a precise method for estimating CWP of principal crops within the Rohri canal command region. Water is a critical determinant of crop productivity because of its essential functions in nutrient absorption and transport, temperature control, and several other aspects. Water productivity was determined as the quotient of the grain yield over the total water utilized by the crop, inclusive of evapotranspiration and also irrigation withdrawals, if applicable. WP indicates how efficiently outputs of crops are obtained per unit of water and is important for measuring the potential of water resource adaptation under climate stress.

Greenhouse Gas Emission Intensity

GHGI was estimated by simulating grain yield and dividing by total greenhouse gas emissions (primarily N_2O from fertilizer and soil processes). It serves as an indicator of efficiency in emissions per unit of food produced. Based on rates of fertilizer application and soil nitrogen transformations, emissions were modeled (see **Fig. 4**).

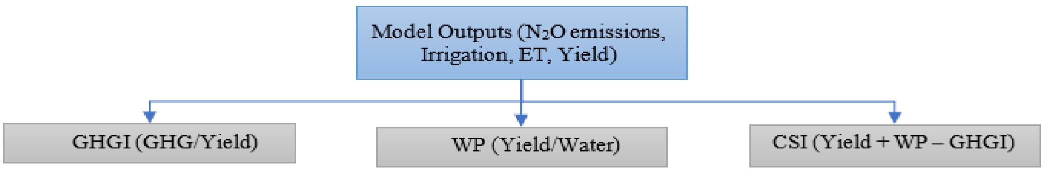

Fig 4. Indicator Calculation Framework.

IV. RESULTS AND DISCUSSION

CSI Under Baseline and Future Scenarios

Fig. 5 illustrates the projected and baseline CSI values for the 3 countries. All these baseline evaluations indicate poor CSI, with average CSI values of approximately −0.19, −0.27, and −0.32, for Zambia, Tanzania, and Malawi, respectively.

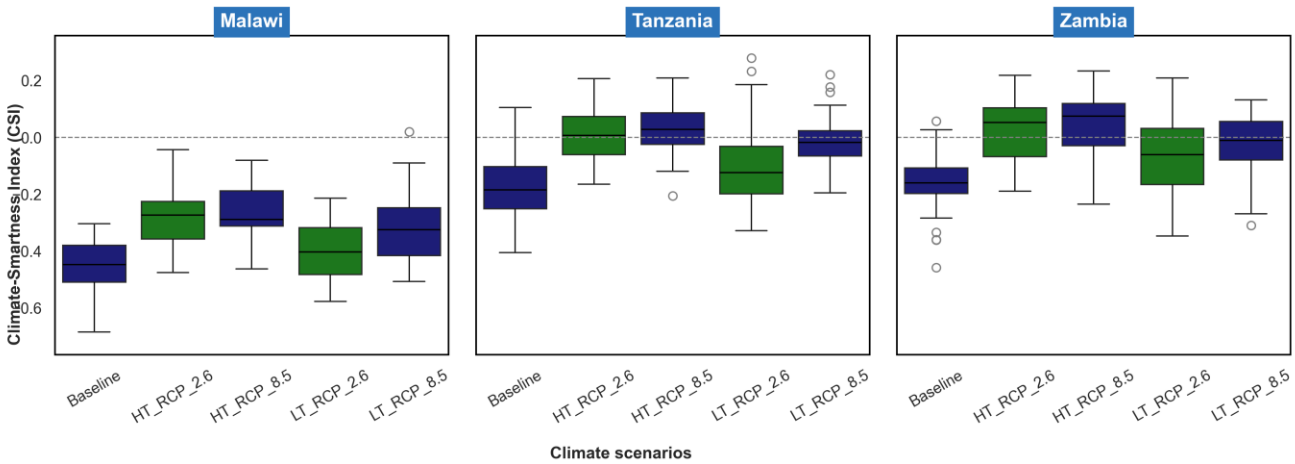

Fig 5. Potential and Baseline Climatic (RCP_2.6 Low Risk, and RCP_8.5 High Risk), and Agro-Technological (Low Technology: LT, and High Technology: HT) CSI Boxplots at National Level.

All LT models resemble the baseline, however with a little rise, facilitated by a minor drop in GHGI. The absence of climate intelligence in baseline and long-term cases is attributable to minimal maize yield, leading to poor water use and elevated greenhouse gas emission levels. Although agriculturalists in SSA produce the least emission per unit field, their very poor yields result in comparatively high greenhouse gas intensities. HT scenarios exhibited mostly favorable CSI, with little variation in CSI values across climatic scenarios (i.e., RCP8.5 vs RCP2.6).

The findings indicate that advanced agricultural technology, instead of global warming, is the primary factor influencing CSI in these cases. This aligns with other literature works that highlighted agricultural and technological advancement as the paramount way to mitigate production discrepancies in SSA. In reference to a study by Nhamo et al. [14], 44.01% of maize harvest in Tanzania may be decreased through the use of cutting-edge technology. The same study done on Zambia by Mwalupaso et al. [15] showed that country level productivity difference was explained 33.02 percent by technical productivity. The high values of CSI linked with HT opportunities are manifested in the significant GHGI reduction and nearly twice the increase of WP. Other model generated data indicate that agro-management that is high input and coupled with better irrigation architecture could reduce the water consumption intensity of staple crop like maize to about 64 percent.

The high yields of the improved use of agro-technology improve both elements of CSI, namely, the reduction of greenhouse gases and water use is optimized with high-tech perspectives. iFEED patterns in all the countries revealed a potential increase in maize output up to three times (206-225) compared to base yield intensities with the use of HT cases. The productivity improvements in maize are 2.91 to about 3.0 tons per hectare in Malawi, 3.2 to 3.31 tons per hectare in Tanzania, and 3.51 to 3.71 tons per hectare in both cases of RCP. HT cases in this work incorporated the implementation of advanced variability that have been found to reduce the productivity deficiency within the study field.

Katengeza and Holden [16] found that maize seedlings which were resistant to drought increased productivity by 44 percent in 6 regions in Malawi. The same results can be recorded in Zambia, which shows that the placement of drought resistant cultivars increases the maize production by 15 percent and increases the stability of the yields. Expectedly, the emission of greenhouse gases increases in high temperature conditions with nitrous oxide emissions increasing by 21 per cent to 47 per cent in both Representative Concentration Pathways, but emissions decline or plateau in low temperature conditions.

The same findings are given by Van Loon et al. [17] who have performed an evaluation of the effects of cropland expansion and intensification with respect to greenhouse gas emissions in 10 countries in SSA, such as Zambia and Tanzania. They state that by meeting the demand of the cereals, there will be an increase in the greenhouse gas emissions of up to 50 percent by the year 2050. SSA could contribute to N_2O emissions 3.5 times more by reducing maize production by about 75 percent, which will increase the entire contribution of the region to global N2O emissions. The production enhancement in HT cases exceeded GHG increases, leading to reduced emissions for every grain. Enhancing agricultural productivity in SSA has been proposed as a viable approach to achieving futuristic food safety while not hindering mitigation actions, which, however, remain a lower precedence in low-income areas such as rural SSA.

Maize Yield Shocks and The Role of Irrigation and Enhanced Varieties

Fig. 6 displays the effects of global warming on maize production fluctuations for RCP8.5 and RCP2.6 in Zambia, including both irrigated scenarios. The average baseline production shock rate is 9.01% (1.9/21 years). Projected weather-driven yield shock level increase to 16% 3.3/21, and 19% 3.9/21 for RCP2.6 and RCP8.5, respectively.

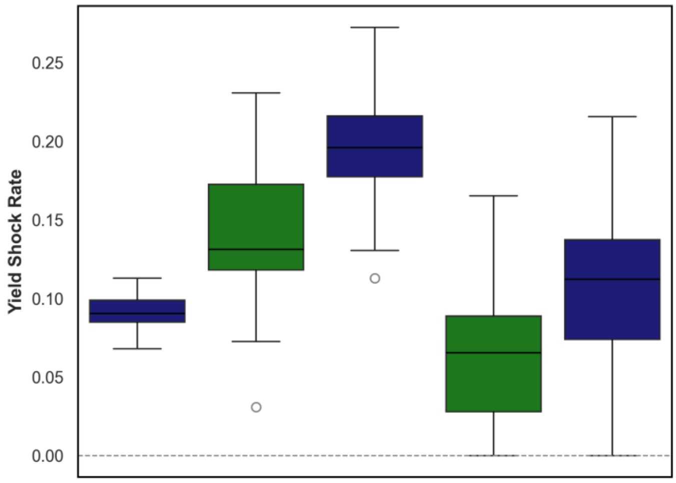

Fig 6. Maize Yields Shock Levels in Zambia.

In Zambia, irrigation is advantageous for both RCP8.5, with a decrease of 4.2%, and RCP2.6, with a decrease of 64% in production shock rates. The decline is more significant in RCP2.6, while increasing temperatures contribute a larger share of yield shock in RCP8.5. Irrigation demonstrates comparable, if diminished, advantages in Tanzania and Malawi. Given that the existing irrigated region constitutes approximately 10% of the possible irrigable land, projected at 2.7 million ha in Zambia, expanding irrigation area will significantly enhance climate-resilient food security. The range across climatic models is shown in boxplots (see **Fig. 6**). Historical (H.) yield shock rate is the percentage of years between 1990 and 2010, which are grouped below the productivity shock limit. The percentage of years ranging from 2050-2060 for irrigated RCP8 is 8.5RFD. Five simulations that fall short of their yield shock limit. 2.6IRR is the percentage of years for weather-driven

RCP2.6 scenarios that fall below their productivity shock limit between 2050 and 2060. 8.5IRR is the percentage of years for weather-driven RCP8.5 scenarios that fall below their productivity shock limit between 2050 and 2060.

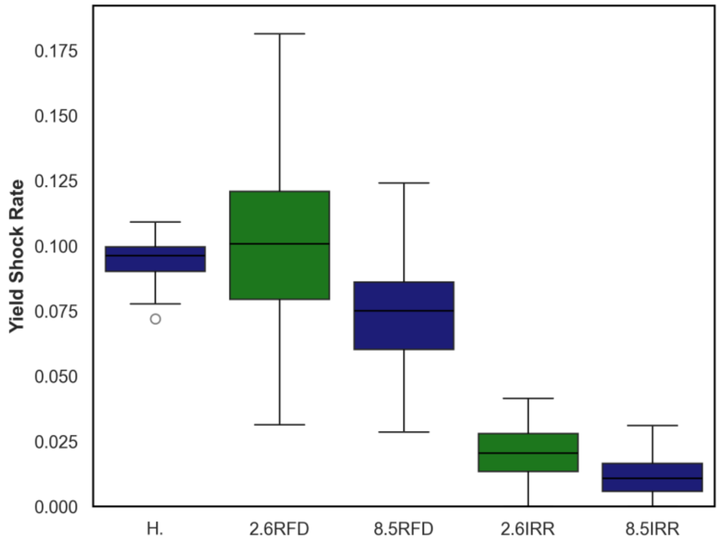

Fig 7. Maize Productivity Shock Levels in Zambia (Novel Crops Compensating Rapid Growth by Mid-20th-Century).

The range across multiple climate models is displayed in boxplots. H. is the historical shock rate (percentage of 1990–2010 years below shock limits). 2.6RFD represents the percentage of rainfed years between 2050 and 2060. They are below their yield shock threshold in RCP2.6 simulations. 8.5RFD is the percentage of rainfed RCP8.5 simulation years between 2050 and 2060 that fall below the shock limit. 2.6IRR is the percentage of years for weather-driven RCP2.6 scenarios that fall below their productivity shock limit between 2050 and 2060. 8.5IRR is the percentage of irrigated RCP8.5 simulated years from 2050 to 2060 that are below the shock limit.

Fig. 7 illustrates the effects of global warming on maize production fluctuations, supposing the development of new crop types in the future that mitigate certain consequences of elevated temperatures by mid-20th-century. It is upgraded maize variabilities and irrigation that alleviate most of the production variability: 87 and 90 per cent in RCP2.6 and RCP8.5 respectively. In Zambia, Tanzania, and Malawi, climate-intelligent frameworks ought to be achieved by enhancing the available agro-technology; however, the countries are likely to encounter serious challenges in the implementation process. Various researches have pointed out the importance of allowance services in the provision of optimal and on time information, which stimulates the use of advanced farming technology, such as upgraded varieties.

On the economic perspective as outlined by Kelly, Adesina, and Gordon [18], there is a need to cover the availability of architectural and cheap agricultural inputs, including improved irrigation, fertilizers and seeds. Financial instruments designed to promote long-term investments or the deployment of subsidies on farming might be better tailored to low-income agriculturalists. The high difference between low-tech and high-tech agriculture results demonstrates the negative impact of the years of inertia in agriculture growth in SSA, as well as highlights the unrealized agricultural potential in the area. The expansion and intensification of the farmland along with the massive deployment of modern farming innovations could allow SSA nations to improve their output and attain food security.

V. CONCLUSION

The research indicates that the greater the level of agro-technology being adopted, the more positive climate-smart outcomes are achieved across the maize systems of Malawi, Tanzania, and Zambia—far more than the effects of climate change. More extreme, high agro-technology scenarios significantly raise the maize yield, improve the water productivity, and reduce the greenhouse gas emissions per grain, and extreme yield shocks are less frequent. On the other hand, low agro-technology scenarios will always be inefficient and more vulnerable. The importance of greater targeted investments in new crop varieties, more irrigation, and greater mechanization and extension services will allow more SSA's potential in agriculture to be unleashed. The adoption of these proposed interventions will promote food security and climate change adaptability in the region.

CRediT Author Statement

The author reviewed the results and approved the final version of the manuscript.

Data Availability

No data was used to support this study.

Conflicts of Interests
The authors declare no conflict of interest.

Funding
No funding agency is associated with this research.

Competing Interests
There are no competing interests.

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ISSN: 3104-4654