

Research Article

Calibration and Evaluation of CERES-Maize and CROPGRO-Dry Bean Crop Simulation Models of the DSSAT in the Great Rift Valley Region of Ethiopia

Theodrose Sisay^{1,2,*} , Kindie Tesfaye³ , Mezegebu Getnet² ,
Nigussie Dechassa⁴ , Mengistu Ketema⁵ 

¹Africa Centre of Excellence for Climate Smart Agriculture and Biodiversity Conservation, Haramaya University, Dire Dawa, Ethiopia

²Ethiopian Institute of Agricultural Research (EIAR), Addis Ababa, Ethiopia

³International Maize and Wheat Improvement Centre (CIMMYT), Addis Ababa, Ethiopia

⁴School of Plant Science, College of Agriculture and Environmental Sciences, Haramaya University, Dire Dawa, Ethiopia

⁵School of Agriculture and Agribusiness, Haramaya University, Dire Dawa, Ethiopia

Abstract

Maize (*Zea mays* L.) is one of the most principal cereal crops ranking first in production in Ethiopia, predominantly produced and consumed directly by the smallholder farmers in the Great Rift Valley (GRV) of Ethiopia. Common bean (*Phaseolus vulgaris*) is also the most important legume crops as the source of protein and export commodity in the GRV. However, the average maize and common bean yields in Ethiopia are still low due to abiotic, biotic and socioeconomic constraints. In this regard, Crop simulation models (CSMs) are used in predicting growth and yield of crops and associated yield gaps under various management options and changing climatic parameters that are profitable with minimal unwanted impacts on the environment. Before using the CSMs, it is necessary to specify model parameters and understand the uncertainties associated with simulating variables that are needed for decision-making. Therefore, the research objective of this study was to calibrate and evaluate the performance of the CERES-Maize and CROPGRO-Dry bean CSMs of the Decision Support System for Agrotechnology Transfer (DSSAT) in the GRV of Ethiopia. The generalized likelihood uncertainty estimation (GLUE) method was used to estimate the genetic parameters of the CSM-CERES-Maize and CROPGRO-Dry bean models. Root mean squared error (RMSE) and Index of agreement (I) were used to evaluate the performance of the models. The DSSAT model reasonably reproduced observations for days to anthesis, days to physiological maturity, and grain yields, with values for the index of agreement of 0.97, 0.88 and 0.61 for CERES-Maize and 0.84, 0.75 and 0.51 for CROPGRO-Dry bean. Similarly, root mean square errors were moderate for days to anthesis (1.2 and 1.2 days), maturity (4.1 and 1.6 days), and yield (0.8 and 1.1 t/ha) for CERES-Maize and CROPGRO-Dry bean, respectively. The model has been successfully calibrated and evaluated for maize and common bean crop varieties and can now it can be taken for further applications in evaluating various crop and soil management options including climate smart agriculture technologies and climate change impact studies.

*Corresponding author: tedy.sisay@gmail.com (Theodrose Sisay)

Received: 23 May 2024; **Accepted:** 24 June 2024; **Published:** 15 July 2024



Copyright: © The Author(s), 2024. Published by Science Publishing Group. This is an **Open Access** article, distributed under the terms of the Creative Commons Attribution 4.0 License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution and reproduction in any medium, provided the original work is properly cited.

Keywords

Crop Simulation Model, DSSAT, Model Calibration, Model Evaluation, Maize, Common Bean, Ethiopia

1. Introduction

Maize (*Zea mays L.*) is the world's third most important crop after rice and wheat [1]. About half of this is grown in developing countries, where maize flour is a staple food for people and maize stalks provide dry-season feed for farm animals. It provides food, feed, and nutritional security in the world's poorest regions in Africa. In Sub-Saharan Africa, maize is a staple food for an estimated 50% of the population and provides 50% of the basic calories [2]. The developing world's demand for maize is expected to rise due to rising food consumption and growing feed needs brought on by population growth [3]. Maize is Ethiopia's largest cereal commodity, ranking first in total production and yield and second in coverage next to tef (*Eragrostis tef*). Due to its widespread significance in the country, maize is one of the strategic field crops targeted to ensure food security in Ethiopia [3]. Maize is grown in sole and/or intercropped with legume crops like common bean. Common bean (*Phaseolus vulgaris L.*) is the most widely produced and consumed legume crop worldwide [4]. It is an important source of income, and nutrition, contributes to the sustainability of human health conditions, and is used as supplemental animal feed [4]. Common bean is used in intensifying crop production in space and species mixture and as soil fertility management, emergency, and security crops in times of failure of cereals and other legumes due to moisture stress [5]. This ecologically and economically significant legume is extensively cultivated and important component of intercropping systems in the Great Rift Valley (GRV) of Ethiopia [6].

Overall maize production has increased over the last decades in Ethiopia, but most of the production increase was due to an increase in agricultural land. The average maize and common bean yields in Ethiopia are still low. Climate change will cause major corn-producing regions to become drier, warmer, and more susceptible to a variety of new pests and diseases [3, 7]. Climate change exacerbates already-existing issues and undercuts initiatives to improve food security and eradicate poverty [8, 9]. The GRV of Ethiopia is a typical example of such ongoing processes.

Understanding the effects of Climate-smart crop production (CSCP) technology options on yields and emissions with various climate periods is mandatory [10-12]. However, understanding this complexity requires the combination of a number of genetic x environment x management (G x E x M) factors, which are difficult to integrate through experimentation [7, 13]. Process-based crop simulation models are increasingly being used in agricultural research and crop and

soil management recommendations [14, 13]. Process-based cropping system models, such as the Crop Simulation Model of the Decision Support System for Agrotechnology Transfer (CSM-DSSAT) [14, 15], are useful tools for evaluating the G x E x M effects [14, 16, 17]. DSSAT requires genetic coefficients, which allow the model to simulate the performance of diverse genotypes under different soil, weather, and management conditions [18].

The CSM-CERES-Maize and CROPGRO-Dry bean [14], use the concept of cultivar coefficients to characterize cultivars. Therefore, before employing such models in decision-making, model parameters must be specified, and the uncertainties related to simulating variables required for decision-making must be understood [16, 19]. Successful use of a crop model depends on the accuracy of calibration and evaluation of different parameters. Crop models must be calibrated such that model parameters truly represent crop characteristics and crop responses to soil and atmospheric conditions based on datasets of soil characteristics, climate, and crop management [20, 16]. After one is confident that the models simulate the real world adequately, computer experiments can be performed hundreds or even thousands of times for given environments to determine how to best manage or control the system. DSSAT was developed to operationalize this approach and make it available for various applications. The objective of this study was, therefore, to estimate the cultivar coefficients for new maize and common bean cultivars and evaluate the CSM-CERES-Maize and CROPGRO-Dry bean models for the GRV region of Ethiopia.

2. Materials and Methods

2.1. Experimental Sites

Field experiments were conducted in the GRV region of Ethiopia at three experimental sites (Melkassa Agricultural Research Centre, Arsi Negele Agricultural sub-center, and Hawassa Agricultural Research Centre hereafter called Melkassa, Arsi Negele and Hawassa, respectively in the main rainy season of 2019). The field experiment was also conducted at Melkassa in the main rainy season of 2020. The purpose of the experiments was to calibrate the CERES-Maize of the CSM-DSSAT.

2.2. Treatments and Experimental Design

Data from these experiments compared plow tillage with full residue removal with no-tillage with 30% crop retention, and three levels (0, 50, 100 kg N ha⁻¹) of N fertilizer at the three experimental sites. A complete factorial split-plot design with tillage assigned to the main plots and N rates to the sub-plots.

2.3. Experimental Materials

The high-yielding maize variety called MH140 was the crop variety selected for the field experiment. In addition, for the common bean crop, Awash miten was selected. Urea was a source of N.

2.4. Treatments and Experimental Design

The experimental design for this study was a split-plot design with four replications with tillage (conventional tillage and minimum tillage) assigned to the main plots and three levels (0, 50, 100 kg N ha⁻¹) of N fertilizer was also applied to the sub-plot as treatments. Conventional tillage involved three tilling without leaving any crop residue, while minimum tillage involves using a row planter to till the field just once while planting and applying 30% of the crop residue. The plot size of 100m² was typical for studies intended for modelling purposes. MH140, a maize variety with a high yield, was utilized. The rows were spaced 0.75 x 0.25 m apart. Urea and diammonium phosphate (DAP) were the fertilizers used.

2.5. Experimental Procedures

Tillage was according to the local practice of tilling three times using the oxen-drawn “maresha” plow. The first and second tillage were, respectively, done in the first and second week of May at Arsi Negele and Hawassa and in the first and second week of June at Melkassa while the third tillage was done at planting time. Planting was from the last week of May to mid-June at Arsi Negele and Hawassa, and in the third and fourth week of June at Melkassa. The maize cultivar was the hybrid MH140. 0.75 x 0.25 m was the inter- and intra-row spacing. The fertilizers used were urea (46-0-0) and diammonium phosphate (DAP, 18-46-0). At the planting stage, 46 kg P₂O₅ ha⁻¹, 41 kg N ha⁻¹, and 23 kg N ha⁻¹ were applied. For the no-tillage plots, glyphosate was sprayed at a rate of 3 L ha⁻¹ two weeks before planting to reduce weeds. Hand weeding was then conducted as needed during crop growth. In tilled plots, weeds were managed with hand hoes.

2.6. Phenology and Yield Data

Data on plant phenological stages (date of seed emergence, date of end of anthesis, and date of physiological maturity) were collected. Dates were noted when 50% of plant population attained a particular stage. Total grain yield was determined from an area of 3 m², oven dried to constant weight and

expressed in dry weight on kg ha⁻¹ basis. Past rainfed national variety trials with MH140 of maize and Awash miten of common bean crop varieties with sufficient records of crop management information for crop growth model evaluation were conducted at Melkassa. Grain yield, days to anthesis and physiological maturity data of 5 years for MH140 and 6 years for Awash miten cultivars were collected from the selected national variety trials conducted at Melkassa. The data were used to calibrate and evaluate CERES-Maize and CROPGRO-Dry bean. For the current study, crop phenology (days to anthesis and days to maturity) and final grain yield during harvest data were obtained from the two years (2019 and 2020) field experiments and multi-year National Variety Trial (NVT) experiments for MH140 of maize and Awash miten of common bean crop cultivars.

2.7. Soil and Weather Data

Daily rainfall, maximum temperature and minimum temperature were obtained from the Ethiopian National Meteorology Institute and the Ethiopian Institute of Agricultural Research (EIAR). Sometimes not all data are available to run a CSM. Therefore, secondary data sources can be used including the National Aeronautics and Space Administration-Prediction of Worldwide Energy Resource (NASA-POWER) Power data portal that contains daily weather data and the harmonized world soil database developed by the International Soil Reference and Information Centre-World Inventory of Soil Emission Potentials (ISRIC-WISE) [19]. Daily solar radiation data were obtained from NASA-POWER (<http://power.larc.nasa.gov>). Soil profile data were obtained from field experiments, secondary sources, and the ISRIC-WISE soil profile database (<https://www.isric.org>).

2.8. Model Calibration and Evaluation

Crop models must be calibrated such that model parameters truly represent crop characteristics and crop responses to soil and atmospheric conditions based on datasets of soil characteristics, climate and crop management. The mean estimated parameters of two seasons (2018 and 2019), under optimal growth conditions, and one season (2018) were used to calibrate the CSM-CERES-Maize and CSM-CROPGRO-Dry bean module, respectively. Cultivar calibration requires the estimation of 6 (Table 1) and 18 (Table 2) genetic coefficient parameters for the CSM-CERES-Maize and CROPGRO-Dry bean modules, respectively. The generalized likelihood uncertainty estimation (GLUE) tool of the DSSAT was used to estimate cultivar specific genetic coefficients for the maize (MH 140) and common bean (Awash miten) cultivars.

Comparing the model's simulated output with the observed data is the process of evaluating a model. This involves assessing the model's performance using a range of statistical methods. Throughout the observational years, the simulated yield and phenological data (days to anthesis and maturity)

were compared with the observed grain yield. The models were tested statistically to assess their performance. [17] The model was evaluated for the days to anthesis, days to physiological maturity, and final grain yield at harvest. The models were evaluated using the 2020 field experimental data and other four years of NVT experimental data for the CERES-Maize model and 5 yr of the NVT experimental data for the CROPGRO-Dry bean model. The performance of the models was evaluated by comparing the simulation output with the observed data using the following goodness-of-fit measures (Eq. 1, 2, and 3).

The coefficient of determination (R^2)

$$R^2 = 1 - \text{RSS}/\text{TSS} \quad (1)$$

Where RSS is the sum of squares of residuals and TSS is the total sum of squares.

R^2 values that are 1 or close to 1 indicate perfect fits between simulated and observed data.

Root mean squared error (RMSE)

$$RSME = \sqrt{\frac{\sum_{i=1}^n (Si - Oi)^2}{n}} \quad (2)$$

where the values in a given year (i) are the simulated and observed values, respectively. A statistical measure of model uncertainty is the RMSE. Values near zero show excellent agreement and, thus, strong model performance.

Index of agreement or d statistic (I)

$$I = 1 - \frac{\sum_{i=1}^n (Si - Oi)^2}{\sum_{i=1}^n (|Si - Sm| + |Oi - Om|)^2} \quad (3)$$

where O_i and S_i are the corresponding observed and simulated values for a certain data set i , and O_m and S_m are the means of the observed and simulated values. Better agreement between the simulated and observed yields is indicated by values nearer 1.

Table 1. Description of genetic coefficient parameters for the DSSAT CERES-Maize model.

Trait	Definition of trait
P1	Degree days (base 8 °C) from emergence to end of juvenile phase
P2	Photoperiod sensitivity coefficient (0-1.0)
P5	Degree days (base 8 °C) from silking to physiological maturity
G2	Potential kernel number
G5	Potential kernel growth rate mg/ (kernel d)
PHINT	Degree days required for a leaf tip to emerge (phyllochron interval) (°C d)

Table 2. Description of genetic coefficient parameters for CROPGRO- Dry bean model.

Trait	Definition of trait
CSDL	Critical short-day length below which reproductive development progresses with no daylength effect (for short day plants) (h)
PPSEN	Slope of the relative response of development to photoperiod with time (positive for short day plants) (1/h)
EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days)
FL-SH	Time between first flower and first pod (R3) (photothermal days)
FL-SD	Time between first flower and first seed (R5) (photothermal days)
SD-PM	Time between first seed (R5) and physiological maturity (R7) (photothermal days)
FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)
LFMAX	Maximum leaf photosynthesis rate at 30 °C, 350 vpm CO ₂ , and high light (mg CO ₂ /m ² -s)
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm ² /g)
SIZELF	Maximum size of full leaf (three leaflets) (cm ²)
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell
WTSPD	Maximum weight per seed (g)

Trait	Definition of trait
SFDUR	Seed filling duration for pod cohort at standard growth conditions
SDPDV	Average seed per pod under standard growing conditions ([seed]/pod)
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)
THRESH	The maximum ratio of (seed/ (seed + shell)) at maturity causes seed to stop growing as their dry weight increases until shells are filled in a cohort
SDPRO	Fraction protein in seeds (g[protein]/g[seed])
SDLIP	Fraction oil in seeds (g[oil]/g[seed])

3. Results and Discussion

3.1. Model Calibration

The genetic coefficients of the maize (MH 140) and common bean (Awash miten) cultivars under investigation are presented in Table 3.

Table 3. Genetic coefficients of maize (MH 140) and common bean (Awash miten) cultivars.

Maize (MH140)		Common bean (Awash miten)			
Parameter	Value	Parameter	Value	Parameter	Value
P1	240.0	CSDL	12.17	SIZELF	135.0
P2	0.700	PPSEN	0.020	XFRT	1.000
P5	810.0	EM-FL	27.0	WTPSD	0.230
G2	750.0	FL-SH	3.5	SFDUR	15.4
G3	8.20	FL-SD	11.0	SDPDV	3.30
PHINT	46.00	SD-PM	23.50	PODUR	6.0
		FL-LF	18.00	THRSH	78.0
		LFMAX	0.99	SDPRO	.235
		SLAVR	270.	SDLIP	.030

3.2. Model Evaluation

The Statistical evaluation results of the simulated against observed days to anthesis, maturity, and yield for MH140 (maize) and Awash Miten (common bean) cultivars is presented in Table 4. For the number of days to anthesis, DSSAT showed good simulation performance. The R² values for days to anthesis were (0.92 for MH140 and 0.78 for Awash miten), the RMSE values for days to anthesis were (1.2 for MH 140 and 1.2 for Awash Miten) and the index of agreement (I) values were (I=0.97 for MH140 and I=0.84 for Awash Miten). There was strong agreement between the simulated and observed days to maturity of maize (0.88 for MH 140 and 0.75 for Awash miten). The R² value for days to maturity were (0.94 for MH140 and 0.74 for Awash Miten). The RMSE value for days to maturity was as low as 4.1 days for MH 140 and 1.6 for Awash Miten cultivars. The 1:1 line graph showing the relationship between observed and simulated for days to anthesis and maturity of the two cultivars are presented in Figure 1. The simulated grain yield agreed with the observed data (I=0.61 and I=0.51 for MH 140 and Awash miten, respectively). The R² values were good (0.86 for MH 140 and 0.95 for Awash Miten). The RMSE values were also moderate (0.8 t/ha for MH 140 and 1.1 t/ha for Awash miten) (Table 4). The 1:1 line graph showing the relationship between observed and simulated yields of the two cultivars are presented in Figure 2. In two of the observation years, yields were somewhat overstated, despite the fact that both models accurately represented the yield variability across the observation period and the long-term observed and simulated yields showed a good match.

Table 4. Statistical evaluation of the simulated against observed days to anthesis, maturity, and yield for MH140 (maize) and Awash Miten (common bean) cultivars.

Variable name	Maize_ MH 140					Common bean_ Awash Miten				
	OBS	SIM	R ²	RMSE	I	OBS	SIM	R ²	RMSE	I
Anthesis (days)	69	69	0.92	1.2	0.97	38	37	0.78	1.2	0.84

Variable name	Maize_MH 140					Common bean_Awash Miten				
	OBS	SIM	R ²	RMSE	I	OBS	SIM	R ²	RMSE	I
Maturity (days)	127	129	0.94	4.1	0.88	80	79	0.74	1.6	0.75
Yield (t/ha)	6.1	6.9	0.86	0.8	0.81	3.4	4.5	0.95	1.1	0.51

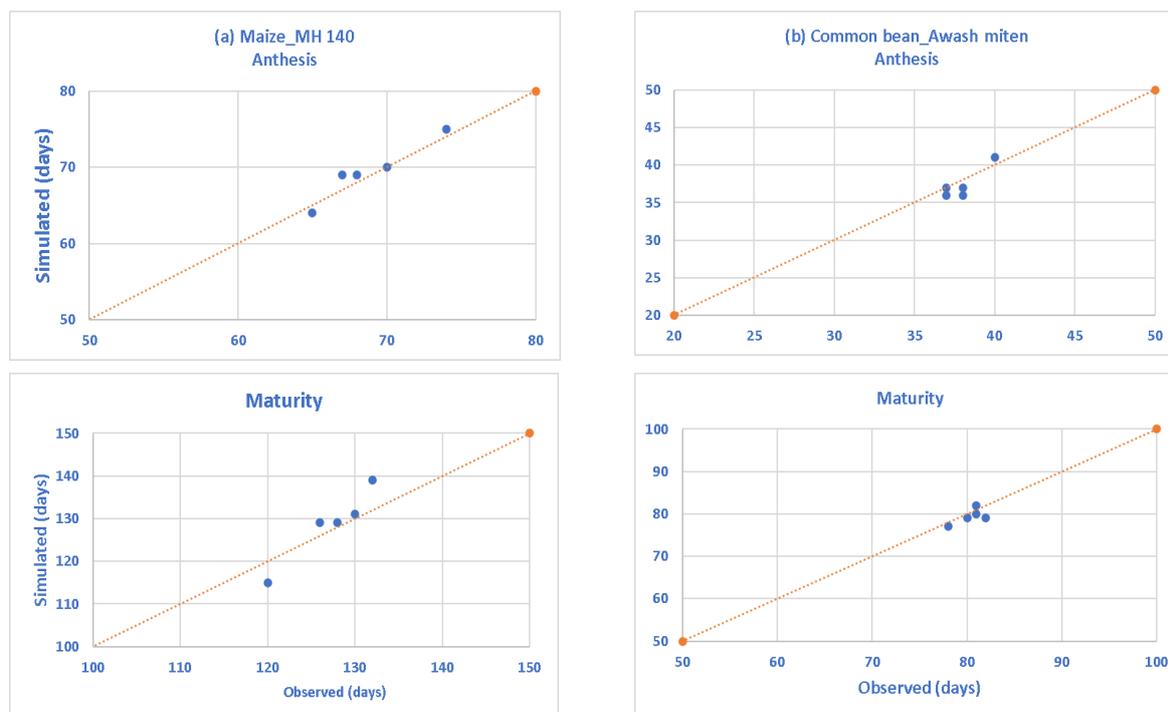


Figure 1. Observed versus simulated days to anthesis and maturity results for (a) the MH140 maize and (b) the Awash miten common bean cultivars.

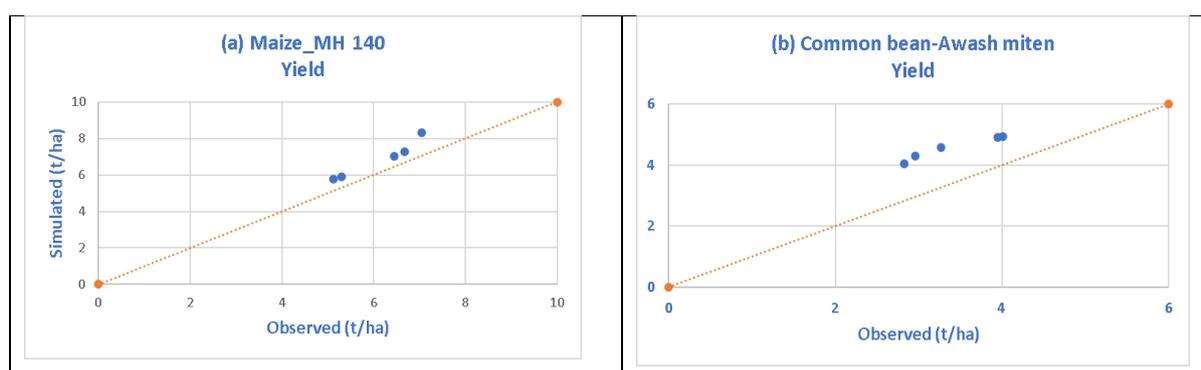


Figure 2. Observed versus simulated yield results for (a) MH140 and (b) Awash Miten cultivars.

4. Conclusions and Recommendations

We calibrated and evaluated the CERES-Maize and CROP-GRO-Dry bean crop simulation models of the DSSAT. The estimated genetic parameter values of the two crop varieties cre-

ated using the GLUE tool of the DSSAT. The models' statistics show that the simulated values agree with the observed ones, suggesting that the model was well calibrated and evaluated. The models can therefore be used to simulate the responses of MH 140 of the maize and Awash miten of the common bean crop varieties to various crop and soil management options including climate smart agriculture technologies in different climate peri-

ods in the great rift valley of Ethiopia.

Acknowledgments

Africa Centre of Excellence for Climate Smart Agriculture and Biodiversity Conservation, Haramaya University, Ethiopia, and EIAR. The research is part of PhD study. The authors also thank the Ethiopian National Meteorology Institute and EIAR for providing weather data free of charge.

Abbreviations

CSM	Crop Simulation Model
CSCP	Climate-Smart Crop Production
DAP	Diammonium Phosphate
DSSAT	Decision Support System for Agrotechnology Transfer
EIAR	Ethiopian Institute of Agricultural Research
GLUE	The Generalized Likelihood Uncertainty Estimation
GRV	Great Rift Valley
NVT	National Variety Trial
RMSE	Root Mean Squared Error

Author Contributions

Theodrose Sisay: Conceptualization, Data curation, Formal Analysis, Methodology, Software, Validation, Visualization, Writing – original draft

Kindie Tesfaye: Conceptualization, Formal Analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing – review & editing

Mezegebu Getnet: Conceptualization, Formal Analysis, Investigation, Software, Supervision, Visualization, Writing – review & editing

Nigussie Dechassa: Conceptualization, Formal Analysis, Funding acquisition, Investigation, Software, Supervision, Visualization, Writing – review & editing

Mengistu Ketema: Conceptualization, Formal Analysis, Investigation, Methodology, Supervision, Validation, Visualization, Writing – review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] WMO, Guide to Agricultural Meteorological Practices, no. 134. 2010.
- [2] K. Tesfaye et al., “Climate Risk Management Potential benefits of drought and heat tolerance for adapting maize to climate change in tropical environments,” *Clim. Risk Manag.*, vol. 19, no. April 2017, pp. 106–119, 2018, <https://doi.org/10.1016/j.crm.2017.10.001>
- [3] T. Abate, B. Shiferaw, A. Menkir, D. Wegary, and Y. Kebede, “Factors that transformed maize productivity in Ethiopia,” pp. 965–981, 2015, <https://doi.org/10.1007/s12571-015-0488-z>
- [4] S. Bakure, T. Yoseph, and D. Ejigu, “Effect of Interrow Spacings on Growth, Yield, and Yield Components of Common Bean (*Phaseolus vulgaris* L.) Varieties in the Central Rift Valley of Ethiopia,” vol. 2023, 2023.
- [5] N. Hailu, C. Fininsa, and T. Tana, “Effect of climate change resilience strategies on productivity of common bean (*Phaseolus vulgaris* L.) in Semi-arid areas of eastern Hararghe, Ethiopia,” vol. 10, no. 15, pp. 1852–1862, 2015, <https://doi.org/10.5897/AJAR2015.9634>
- [6] M. S. Teshome, Abebe, Yared D., “Determinants of Productivity and Profitability Performance of Smallholder Common Bean Producers in Central Rift Valley of Etiyopya Merkezi Rift Vadisinde Küçük Ölçekli Fasulye Üreticilerinin Verimlilik ve Karlılık Performansının Belirleyicileri,” vol. 5, no. 1, pp. 27–48, 2021.
- [7] M. Getnet, K. Descheemaeker, M. K. van Ittersum, and H. Hengsdijk, “Narrowing crop yield gaps in Ethiopia under current and future climate: A model-based exploration of intensification options and their trade-offs with the water balance,” *F. Crop. Res.*, vol. 278, no. October 2021, p. 108442, 2022, <https://doi.org/10.1016/j.fcr.2022.108442>
- [8] IPCC, “Future Global Climate: Scenario-based Projections and Near-term Information,” 2021, pp. 553–672.
- [9] WMO, State of the Climate in Africa, no. 1275. 2021.
- [10] FAO, “Ethiopia Climate-Smart Agriculture Scoping Study,” 2016.
- [11] FAO, Climate-smart agriculture Sustainable Development Goals. 2019.
- [12] H. C. Jansen et al., “Land and water resources assessment in the Ethiopian Central Rift Valley,” *Alterra Wageningen UR*, no. July 2007, p. 44, 2007.
- [13] D. B. R. and O. E. K. Tesfaye, A. Khatri-Chhetri, P. K. Aggarwal, F. Mequanint, P. B. Shirsath, C. M. Stirling, M. L. Jat, “Assessing climate adaptation options for cereal-based systems in the eastern Indo-Gangetic Plains, South Asia,” *J. Agric. Sci.*, 2019.
- [14] J. W. Jones et al., The DSSAT cropping system model, vol. 18, no. 3–4. 2003.
- [15] A. Araya, P. V. V Prasad, P. H. Gowda, Z. Zambreski, and I. A. Ciampitti, “Science of the Total Environment Management options for mid-century maize (*Zea mays* L.) in Ethiopia,” *Sci. Total Environ.*, vol. 758, p. 143635, 2021, <https://doi.org/10.1016/j.scitotenv.2020.143635>
- [16] J. M. Yang, J. Y. Yang, S. Liu, and G. Hoogenboom, “An evaluation of the statistical methods for testing the performance of crop models with observed data,” *Agric. Syst.*, vol. 127, pp. 81–89, 2014, <https://doi.org/10.1016/j.agsy.2014.01.008>

- [17] M. Roja, M. K. Gumma, and M. D. Reddy, "Crop modelling in agricultural crops," *Current Science*, vol. 124, no. 8, pp. 910–920, 2023, <https://doi.org/10.18520/cs/v124/i8/910-920>
- [18] G. Hoogenboom, J. W. Jones, P. C. S. Traore, and K. J. Boote, "Improving Soil Fertility Recommendations in Africa using the Decision Support System for Agrotechnology Transfer (DSSAT)," in *Improving Soil Fertility Recommendations in Africa using the Decision Support System for Agrotechnology Transfer (DSSAT)*, 2012, pp. 9–18.
- [19] P. Rugira, J. Ma, L. Zheng, C. Wu, and E. Liu, "Application of DSSAT CERES-Maize to Identify the Optimum Irrigation Management and Sowing Dates on Improving Maize Yield in Northern China," 2021.
- [20] A. Cravero, S. Pardo, P. Galeas, J. López Fenner, and M. Caniupán, "Data Type and Data Sources for Agricultural Big Data and Machine Learning," *Sustain.*, vol. 14, no. 23, pp. 1–37, 2022, <https://doi.org/10.3390/su142316131>