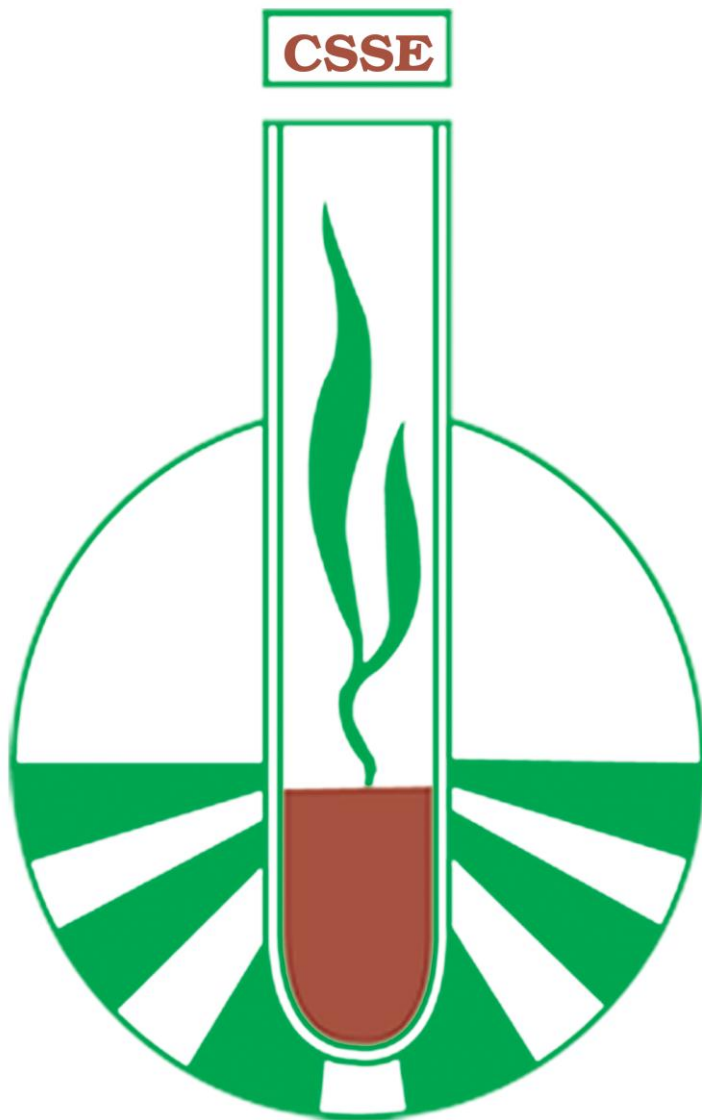


Ethiopian Journal of Crop Science

Volume 8

Number 2 (2020)

ISSN: 2072-8506



An Official Journal of the Crop Science
Society of Ethiopia (CSSE)

2020
Addis Ababa, Ethiopia

Ethiopian Journal of Crop Science

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Ethiopian Journal of Crop Science

Published by the Crop Science Society of Ethiopia (CSSE)

Vol. 8 Number 2 (2020) ISSN 2072-8506

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Ethiopian Journal of Crop Science (EJCS)

Volume 8, Number 2, 2020

ISSN 2072-8506

Addis Ababa, Ethiopia

Ethiopian Journal of Crop Science

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Table of Contents

Assessment of the Potential Impacts of Climate Change in Agricultural Catchment: The Case of Fincha, North western Ethiopia <i>Wakjira Takala Dibaba, Tamene Adugna Demissie and Konrad Miegel</i>	1
Artificial Intelligence Assisted Early Blight and Late Blight Potato Disease Detection Using Convolutional Neural Networks <i>Natnael Tilahun and Beakal Gizachew</i>	15
Genetic Variability and quantitative traits inheritance in Sesame (<i>Sesamum indicum</i> L.) Genotypes <i>Feyera Takele, Dagnachew Lule and Sentayehu Alemereew</i>	29
Trends in Observed Temperature and Rainfall Variability in Major Potato Growing Districts of Eastern Ethiopia <i>Simeret Burga, Kindie Tesfaye, Nigussie Dechassa, Tamado Tana and Wassu Mohammed</i>	43
Yield Stability Analysis of Soybean Varieties (early set) in Western Oromia, Ethiopia <i>Adane Arega, Alemayehu Dabessa and Solomon Bekele</i>	67
Genotype by Environment Interaction and Grain Yield Stability of Striga Resistant Sorghum [<i>Sorghum bicolor</i> (L.) Moench] Genotypes in Ethiopia <i>Fantaye Belay, Firew Mekbib and Taye Tadesse</i>	79
The Release and Registration of Bako-09 (Acc. 214995) Finger millet Variety <i>Kebede Dessalegn, Dagnachew Lule, Kassa Mamo, Girma Mengistu, Girma Chemed, Megersa Debela, Megersa Kebede, Chemed Birhanu, Hailu Feyisa, Geleta Gerema, Fufa Anbessa and Gudeta Bedada</i>	101
The Release and Registration of Gute (Late Set) Soybean Varieties <i>Adane Arega and Alemayeh Dabessa</i>	107
Guidelines for Contributors	113

Assessment of the Potential Impacts of Climate Change in Agricultural Catchment: The Case of Fincha, North western Ethiopia

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Abstract

The relevance of agriculture to the promotion of sustainable development largely depends on the availability of water resources. Climate change affects water resource by altering the magnitude and patterns of hydrological process. This study was aimed at evaluating the potential impacts of climate change on hydrological process of Fincha catchment, upper Blue Nile basin. The ensemble mean of regional climate models (RCMs) in coordinated regional climate downscaling experiment (CORDEX)-Africa was used based on high emission scenario (RCP8.5) and medium emission scenario (RCP4.5). Soil and Water Assessment tool (SWAT) hydrological modeling was used to evaluate the impacts of climate change. The result shows a decreasing precipitation by -8.24% to -11.32% under RCP4.5 and -7.87% to -9.67% under RCP8.5 in 2021-2050 and 2051-2080, respectively. The temperature will increase under both RCPs. The decline of precipitation and increase of temperature reduces surface flow, groundwater and water yield. The increase in Evapotranspiration due to increased temperature and higher evaporation demands coupled with a decreasing precipitation leads to a reduced soil moisture. This could reduce the availability of water for crop production, which will be a chronic issue to the subsistence agriculture. The increase in seasonal and annual variation of precipitation and temperature increased the frequency of hot and dry years that will lead to serious water scarcity that aggravate water stress in the catchment and further downstream. Consequently, strong mitigation and adaptation through land and water management by coping with water scarcity in agriculture and water productivity is indispensable to manage the risks.

Keywords: Ensemble, Fincha, Rainfall, RCMs, water resources

Introduction

Land and water resources are fundamentally linked to the global and regional challenges of food security, degradation and depletion of natural resources (FAO, 2011) owing to their

pivotal role for agriculture production, urban and rural developments. However, the global and regional climate changes have become the major threats of the resources. This change is expected to produce detrimental environmental effects such as lowering potential productivity,

which is essential for productive and resilient agricultural systems and declines the products and services of the livelihood.

Climate change hampers agricultural yields through disturbing the agro-ecological environment (Chhogyel & Kumar, 2018; Raza *et al.*, 2019) and exacerbates the current stress of water resources availability (Bates *et al.*, 2008). This spurred an interest into the effects on water resources on which many nations like Ethiopia are preferring their development activities.

Regardless of the changes in climate and its impacts, different studies projected climate changes with different degrees of change. Dile *et al.* (2013) in Gilgel Abay projected a decreasing precipitation during 2010-2040 but increases in 2070-2100 while Shiferaw *et al.* (2018) on Ilala watershed reported an increasing temperature, however rainfall does not show significant change. Recent study in Rift valley revealed a decreasing precipitation and increasing temperature (Gadissa *et al.*, 2018). It can be seen, temperature is increasing however there is no consensus among studies on the direction of the projected precipitation. Overall, the studies revealed the climate change impacts on future seasonal and annual hydrological variables is increasing stresses of water resources availability. However, how climate change continues to interact and disturb the land and water resources varies from global to region and region to local scales. Hence, research that could

improve our understanding of the extent to which climate change affects the regional water resources, agriculture and environment is vital.

In recent past, rapid population growth with the expansion of commercial farm, deforestation and cultivation lands coupled with rapid urban expansion in Finchaa catchment have brought severe land and water resources degradation (Dibaba *et al.*, 2020a). Furthermore, the highly rising demands of water in Finchaa catchment owing to the socio-economic progresses and high demand of irrigation water for sugarcane cultivation are increasing pressure on water resources of the catchment.

The regional to local information on climate change helps to define susceptibility of the land and water resources and reveals the process and mechanisms of regional changes that could help to plan appropriate management system (Shawul *et al.*, 2019). In this study, an integrated approach of climate change modeling and hydrological modeling was used to assess the climate change at catchment level and explore the potential impacts of the changes in Finchaa agricultural dominated catchment.

Materials and Methods

Study area

The study area, Finchaa is an agricultural catchment in North western part, Oromia Regional State,

Ethiopia. The catchment is mainly characterized by agricultural land with some range lands around the downstream of the catchment and wetlands around the head of Abay Chomen reservoir, upstream of the

catchment. Geographically the catchment is located in 9°10' to 10°00' North latitude and 37°00' to 37°40' East longitude with a total area of 3781km². The description of the study area is shown by Figure 1.

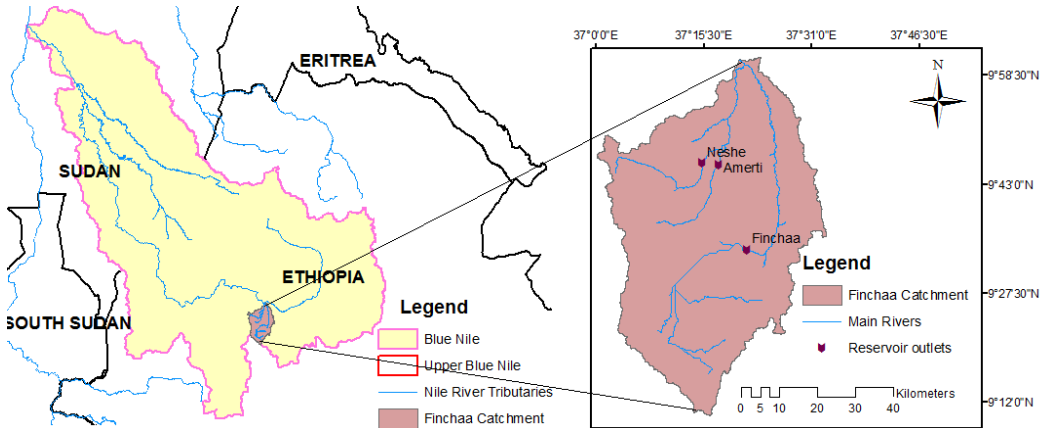


Figure 1. Map of the study Area

Agriculture is the major activity and occupation of the community in Finchaa catchment. Although most of the community in Finchaa catchment is depending on agriculture, farming system in the catchment is constrained by the complex topography, soil and land degradation and variability environmental changes (Dibaba *et al.*, 2020a; Tefera & Sterk, 2010)

Data collected

The study used spatial (DEM, soil and land use/land cover), temporal (meteorological and hydrological) and Regional Climate Models data. Digital Elevation Model (DEM) of 30m x 30m downloaded from the United States Geological Survey (USGS) at <https://earthexplorer.usgs.gov/> was used for watershed delineation, slope and

physical catchment characteristics generation. The soil data required for the study was collected from the Ministry of Water, Irrigation and Electricity, and classified according to the FAO classification system. The land use/land cover data of 2017 derived from Landsat 8 operational land imager (OLI) used in this study was developed by Dibaba *et al.* (2020a).

The observed meteorological data from five weather stations inside the catchment was collected from the National Meteorological Service Agency (NMSA) of Ethiopia. These stations were selected based on their record length and percentage of missed data. Inverse Distance Weighting (IDW) was used to the

missing data values of the stations. A stream flow data was collected from the Ministry of Water, Irrigation and Electricity hydrology department for the years 1987-2007.

Methodology

Climate change scenarios and their impact assessment

Four Regional climate models (CCLM4-8, HIRHAM5, RACMO22T and RCA4) showing better performance were selected after evaluating the performance of six Regional Climate Models used in Coordinated Regional Climate Downscaling Experiment (CORDEX) Africa. The detail evaluation of the CORDEX-RCMs in Finchaa catchment presented by Dibaba et al. (2019) indicated, the ensemble mean outperforms the individual RCMs.

The evaluation of the climate change was based on two future periods denoted by near future (2021-2050) and mid-future (2051-2080) with a baseline/historical period of 1986-2015 under mid-range mitigation emission scenario (RCP4.5) and high emission scenario (RCP8.5). The RCMs output from CORDEX-RCMs were bias corrected against the

observed precipitation and temperature using the distributed mapping technique in climate model data for hydrological modeling (CMhyd). Then, the potential impacts of the climate change under the historical and future scenario was assessed using Soil and Water assessment tool (SWAT) model.

Soil and Water Assessment Tool

The SWAT is a physically based semi-distributed model that drives on a continues time scale at catchment scale (Arnold *et al.*, 1998). SWAT Model was developed to simulate the impact of land management and climate change on hydrology, sediment, water quality and nutrients over long periods in agricultural watersheds on daily, monthly and yearly bases. The SWAT predicts the hydrological process at each hydrological response unit (HRUs) based on the water balance equation (Neitsch et al., 2011) given in equation 1. The catchment is divided into sub-basins that contain one or more HRUs. The HRU is the smallest unit for the catchment physical process discretized based on the homogeneity of the land use, soil type and slope classes.

$$SWt = SWo + \sum_{i=1}^t (Rday - Qsurf - Ea - Wseep - Qgw) \quad (1)$$

Where, SWt is the final soil water content(mm), SWo is the initial water content(mm), t is the time(days), $Rday$ is the amount of precipitation on day

$I(mm)$, $Qsurf$ is the amount of surface runoff on day I (mm), Ea is the amount of evapotranspiration on day $I(mm)$, $Wseep$ is the amount of water

entering the vadose zone from the soil profile on day I(mm) and Q_{gw} is the amount of return flow on day I (mm).

The model allows the simulation of different hydrological and physical process occurring in the watershed (Neitsch et al., 2011). The major model outputs are primarily discharge of the major and tributary streams with water balance components of the watershed.

SWAT Performance Evaluation

Sensitivity Analysis, Calibration and validation

Sensitivity analysis is done with the aim of identifying the most influencing parameters on the model output. The Calibration and Uncertainty Program (SWAT-CUP) used the Sequential Uncertainty Fitting (SUFI-2) program for sensitivity

analysis, calibration and validation (Abbaspour, 2015). Calibration process involves the estimation of model parameters by comparing the model prediction with the observed data under the same condition (Moriassi *et al.*, 2007, Abbaspour, 2015). Validation is testing the calibrated model without further parameter adjustments in an independent dataset. The observed stream flow data of 1987-2007 was split into a warm-up (1987-1989), calibration (1990-2000) and validation (2001-2006) period.

The evaluation of the predictive capability of the SWAT simulation with respect to the observed stream flow was expressed by coefficients of determination (R^2) and Nash-Sutcliffe efficiency (NSE). The higher R^2 value indicates less error. NSE ranges from negative infinity to 1(best). These statistics are calculated using equations 2 to 3.

$$R^2 = \frac{\sum_{i=1}^n [(Q_{mi} - \bar{Q}_m)(Q_{si} - \bar{Q}_s)]^2}{\sqrt{\sum_{i=1}^n (Q_{mi} - \bar{Q}_m)^2 \sum_{i=1}^n (Q_{si} - \bar{Q}_s)^2}}; 0 \leq R^2 \leq 1 \quad (2)$$

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{mi} - Q_{si})^2}{\sum_{i=1}^n (Q_{mi} - \bar{Q}_m)^2}; -\infty \leq NSE \leq 1 \quad (3)$$

Where Q_m is the measured discharge, Q_s is the simulated discharge and $\bar{Q}_m$ is the average measured discharge and $\bar{Q}_s$ is the average simulated discharge.

Result and Discussion

Sensitivity analysis, calibration and validation of the SWAT model

The most sensitive parameters of flow prediction was SCS runoff curve

Table 1. Sensitivity analysis and calibrated parameters

Par	Parameter Name	File type	Sensitivity		Sensitivity Rank	Calibration	
			t-Stat	P-Value		Parameter value range	Fitted Value
1	r_CN2	.mgt	-18.58	0.00	1	±25%	-1.548%
12	r_SOL_AWC	.sol	-4.79	0.00	2	±25%	4.62%
2	a_RCHRG_DP	.gw	-3.40	0.00	3	0-1	0.008
9	v_CH_K2	.rte	-2.22	0.03	4	5-130	107.71
4	a_GW_DELAY	.gw	-1.79	0.07	5	±10	-4.342
3	v_ALPHA_BF	.gw	1.47	0.14	6	0-1	0.449
15	v_SLSUBBSN	.hru	-0.83	0.41	7	10-150	71.909
6	a_GW_REVAP	.gw	-0.58	0.56	8	±0.036	0.0004

Key: r-denotes multiplying initial parameter value by its percent, v-replacement of the initial value of the parameter, a-adding value to initial parameter value

number-CN2, (runoff process), followed by soil available water capacity-SOL_AWC (soil parameter) and deep aquifer percolation fraction-RCHRG_DP (groundwater parameter (Table 1). The most sensitive parameters, curve number and soil available water capacity in the catchment are directly related to the land use/land cover and soil characteristics.

The SWAT calibration revealed that the model was able to capture the observed stream flow with R^2 and NSE of 0.71 and 0.71 respectively. The validation of the model also shows a good agreement with R^2 and NSE of 0.81 and 0.76 respectively. In general, the calibration and validation

results showed fairly good agreement between the simulated and observed flow (Figure 2). Hence, SWAT model is good enough to be used in planning watershed modeling of Finchaa catchment as the model simulation captured the observed flow of the catchment.

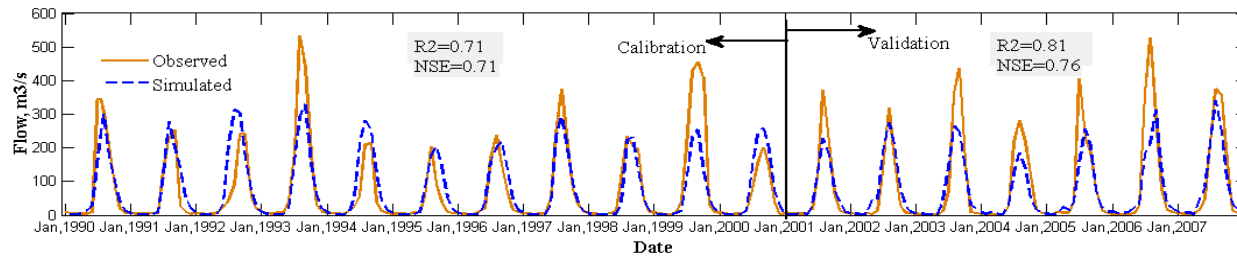


Figure 2. Calibration and validation of average monthly stream flow

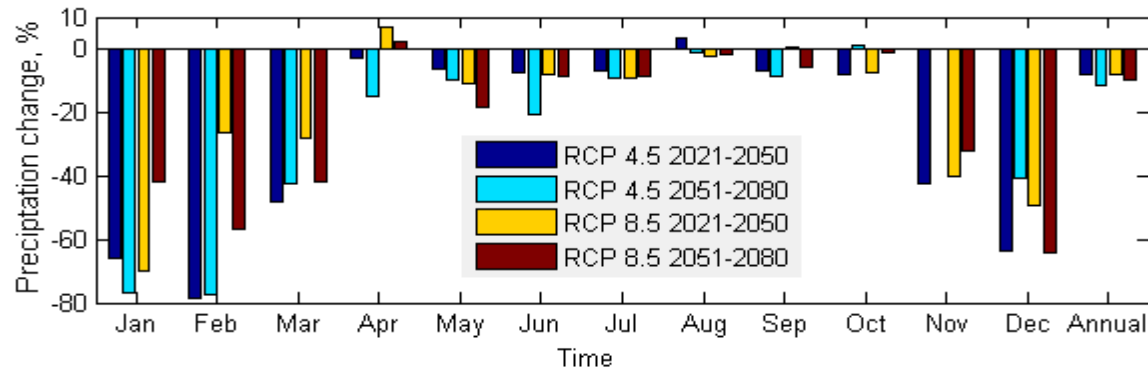


Figure 3. Seasonal changes of precipitation change in Finchaa catchment (Dibaba et al., 2020b).

Climate change projections of Ensemble RCMs

Climate change was evaluated in terms of the annual and seasonal changes of precipitation, maximum and minimum temperature. Accordingly, the change in precipitation varies from -8.24% under RCP4.5 to -7.87% under RCP8.5 in near future and varies from -11.32% under RCP4.5 to -9.67% under RCP8.5 in the mid future. Overall, the ensemble mean of the RCMs projection shows, precipitation declines under all scenarios.

The seasonal precipitation decline is higher in the dry season than wet season. The seasons that experience the highest precipitation in the catchment (JJAS) experiences lower decline of precipitation. The dry seasons will experience a higher decreasing precipitation under all scenarios (Figure 3).

A study by Seleshi & Camberlin (2006) also reported a decreasing trend of precipitation intensity using data from 1965 to 2002 in eastern, southwestern and southern regions of Ethiopia. The results of decreasing precipitation projections are consistent with the results presented by climate change studies (Dile et al., 2013, Gadissa et al., 2018). However, there are also studies that projected a decreasing precipitation over Upper Blue Nile River basin. Using statistical downscaling techniques, Mekonnen & Disse (2018) projected increasing trends of precipitation by 1 to 14.4%.

Similarly, Gebre & Ludwig (2015) reported an increase of future precipitation over Tana basin. Although there are studies that projected an increase in precipitation, the observed precipitation of the last century showed a decrease of precipitation over Africa (IPCC, 2013). From 17 climate models, most of them (10) reported reduction than increases (7) (Elshamy, Seierstad, & Sorteberg, 2009). The differences among the climate change studies could be due to the techniques of downscaling, types and resolution of GCM-RCMs combinations and their associated boundary conditions.

The projection of maximum and minimum temperature shows, both temperature will increase under all scenarios. Accordingly, the change in maximum temperature varies from 1.34°C under RCP4.5 to 1.49°C under RCP8.5 in near future and from 2.15°C under RCP4.5 to 3.21°C under RCP8.5 in mid future. Similarly, the change in minimum temperature varies from 1.57°C under RCP4.5 to 1.92°C under RCP8.5 in near future and from 2.67°C under RCP4.5 to 4.23°C under RCP8.5 in mid future.

Although the change in projection of both maximum and minimum temperature shows increasing trend, the changes vary with the emission scenario and the future periods. The temperature change is higher for higher emission scenarios (RCP8.5) than medium emission scenarios (RCP4.5) and higher in the mid future (2051-2080) than the near future

(2021-2050). This confirms RCP8.5 is warmer than RCP4.5. Further, the analysis of the temperature change reveals, the increase of the daily minimum temperature is higher and more rapidly than daily maximum temperature leading to the increase of the daily mean temperature.

The variation in changes of temperature is not only limited to

annual, rather temperature change also varies seasonally. Like the magnitude of the changes, the seasonal variations are higher for minimum temperature than maximum temperature. Wet seasons are expected to have higher minimum temperature change than the dry seasons as shown by Figure 4.

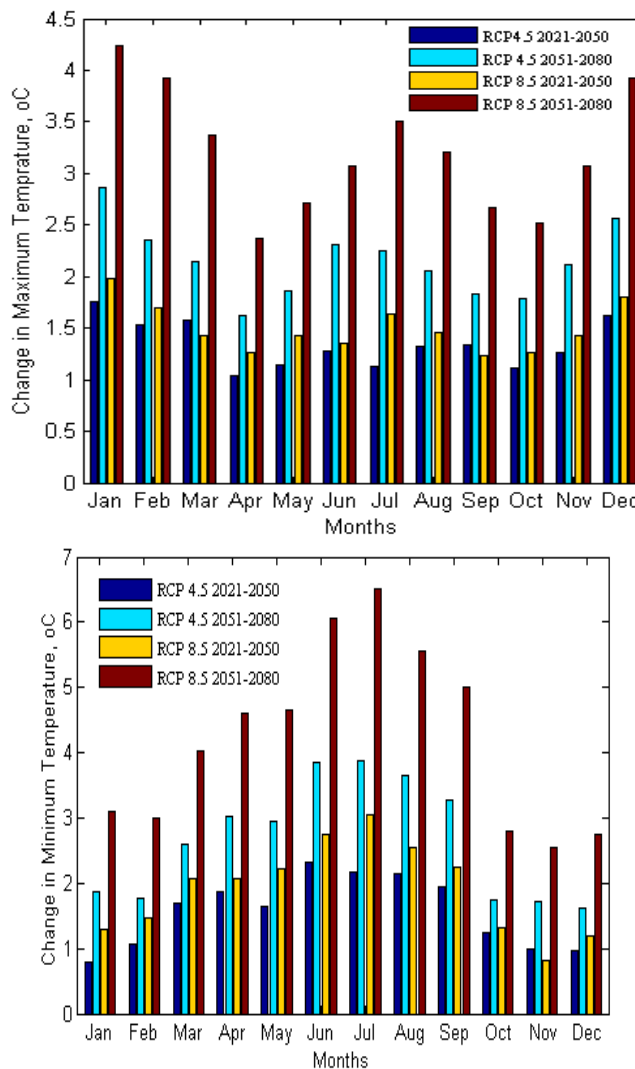


Figure 4. Seasonal changes of maximum temperature and minimum temperature.

Climate change studies in Ethiopia reported similar trends of temperature change but with varying degrees based on the downscaling techniques and types of climate model. GFDRR (2011) reported mean annual temperature is projected to increase by 1.1 °C to 3.1 °C by the 2060 and 1.5 °C to 5.1 °C by 2090s. Likewise, Beyene et al, (2010) reported increasing annual temperature from 0.91 °C to 1.9 °C during 2010-2039 using the ensemble of 11 GCMs over upper Blue Nile basin.

Overall, it can be seen temperature is increasing however there is no harmony among studies on the direction of the projected precipitation. The complexity in nature of precipitation and its dependency on topographic and physical factors coupled with high inter-annual and inter-decadal variability of rainfall in Ethiopia could contribute to this. Hence, the use of multiple GCM-RCMs could help in improving the uncertainties of climate models associated with individual RCMs.

The potential impacts of climate change

The decline of precipitation and increase of temperature lead to a reduced surface runoff (SQ), groundwater (GW) and overall water yield (WY) while potential evapotranspiration (PET) gets increased under both scenarios (Figure 5). The decline of SQ ranges from -7.33% under RCP4.5 in near future to -14.48% under RCP4.5 in mid future. Whereas, the decline of GW varies from -9.21% under RCP4.5 in near future to -15.86% under RCP8.5 in mid future. The decline of WY yield varies from 8.49% under RCP4.5 in near future to -13.77% under RCP4.5 in mid future. Whereas, the increase in PET varies from 16.31% under RCP4.5 in near future to 22.89% under RCP8.5 in mid future. The increase in evapotranspiration is attributed by the increase in vapor pressure deficit owing to the higher temperature and the increase of PET could be the factor for the decline of WY.

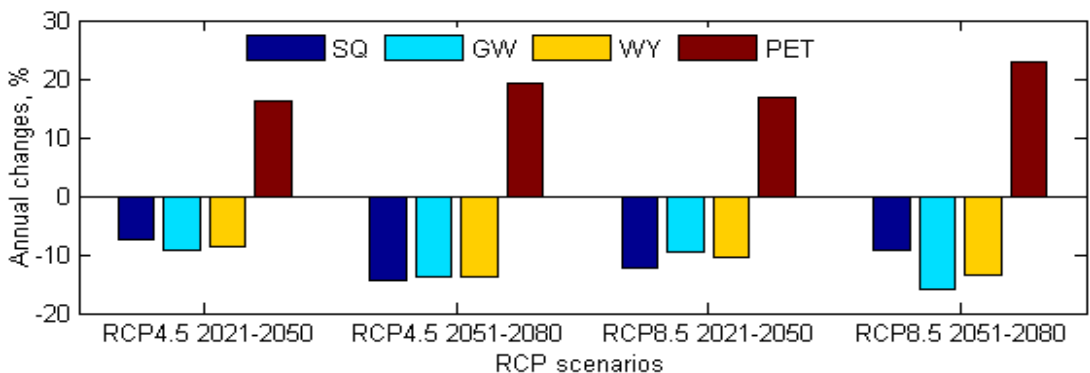


Figure 5. Changes of water balance components under a climate change

Although climate change affects both surface water and groundwater, assessment of climate change impacts on GW is difficult as it requires further subsurface investigation. However, it can be noticed that any variation of the precipitation with changes in vegetation, temperature and evapotranspiration affects GW recharge. However, the rates of changes in GW due to climate change are more likely slow than changes in surface water.

Generally, the potential impacts of climate change are changes in stream flow and runoff characteristics, altered frequency and distribution of precipitation patterns, altered GW recharge and discharge rates and increased atmospheric evaporative demand-changes in evapotranspiration process. This alters flow regime and change nutrient and sediment budgets of watersheds and decreases water availability affecting vegetation survival and growth. The overall decline of annual flow is mainly due to the decline of the seasonal flows as stream flow is mainly controlled by seasonal patterns of precipitation and temperature. The warmer and drier seasons projected under both scenarios could increase the amount and magnitude of low flow days that further aggravate water stress in the catchment and downstream. Similar study in Blue Nile basin also revealed, the seasonal and annual variation of the future temperature shows the increased hot and dry years that will lead to serious water scarcity (Coffel et al., 2019).

Climate change studies on sub-Sahara also confirmed similar findings of warming trends of climate projections in inland subtropics, increasing aridity and changes in rainfall (Serdeczny et al., 2016). Beyene et al. (2010) on Nile River reported a decline of flow during the mid-2040-2069 due precipitation decline and increased evaporation demand. Using ensemble of five GCMs, Shiferaw et al., (2018) also confirmed the decline of the projected surface runoff under both RCPs due to the climate change. The extreme temperature which is either above or below the thresholds at critical times during the development also affects plant growth, plant reproductive process and pollination stage of fruit set (Hatfield & Prueger, 2015). In general, the effects of temperature change through increased water deficits highly affects the availability of water for crop production, which is chronic to the farmers in the catchment whose livelihood is based on agriculture.

In the study area, we have compared the combined effects of land use/land cover and climate change, and found that the impacts of climate change is more decisive than the impacts of land use/land cover (Dibaba et al., 2020b). However, uncertainties are pertinent to models. In this regard, this study should not be used as the actual result but as the indicators of future climate changes and water balance components with invaluable insights on the risk assessment of climate change on Finchaa catchment.

Conclusion

The ensemble mean of the RCMs projection shows, annual precipitation declines under all scenarios. The seasonal changes of precipitation shows, seasons that experience the highest precipitation is expected to have lower decline of precipitation than the dry seasons. The projections of the temperature change show the increase of the daily minimum temperature is higher and more rapidly than daily maximum temperature.

Changes in stream flow and runoff characteristics, altered frequency and distribution of precipitation patterns, altered groundwater recharge and increased atmospheric evaporative demand-changes in evapotranspiration process are the major potential impacts of climate change. The seasonal patterns of precipitation and temperature added with the catchment physical characteristics controls stream flow. The warm and dry seasons projected under both scenarios could increase the amount and magnitude of low flow days. Consequently, the catchment is highly exposed to the potential impacts of climate change that could range from warming to crop failures as a result of prolonged dry seasons.

The study provided important information on the relative influences potential climate change in agricultural catchment. This helps to plan the proper water resources management interventions. Especially if the degraded sloppy lands are

rehabilitated, the ground recharge will increase and surface runoff which washes the top soil in to the lakes will get reduced. In general, the result highlights the need for regional developments and cooperation to urge for strong climate resilient management strategies for the rapid climate changes in the catchment.

Relatively, the regional projections of drought and soil moisture remain uncertain in comparison to the other components of hydrological process. Hence, assessing how climate change affects soil moisture and drought needs to be studied in the area.

Acknowledgements

We would like to thank Rostock University, Jimma University, and the Centre of Excellence in Science and Technology, Ethiopia, for providing resources and material supports for the study. The RCMs data are obtained from the <https://climate4impact.eu/impactportal/data/esgfsearch.jsp>. We thank the world climate Research Program (WCRP), IS-ENES Climate4Impact for providing the data sets of the Coordinated Regional Downscaling Experiment (CORDEX). We also thank the National Meteorological Agency for providing observed climate data.

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Artificial Intelligence Assisted Early Blight and Late Blight Potato Disease Detection Using Convolutional Neural Networks

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Abstract

Developing countries like Ethiopia have resources suitable for the production of different varieties of crops. Potato is the fourth as a major crop in the world, after rice, wheat, and maize. In Ethiopia, one of the crops produced and consumed in mass is potatoes. Nonetheless, the yield per unit area of potatoes is very low compared to other countries. There are a plethora of reasons and one of them is potato disease. The major disease, which affects the major potato production area is late blight, according to researchers on the field estimated losses range from 6.5 to 67.7% depending on the accessibility of varieties. As plant pathologists mentioned not to take early late blight disease management would destroy the whole farm within a few days. For decades many researchers have experimented on plant disease detection and classification using computer vision via different approaches and algorithms. Most researchers used traditional machine learning algorithms that require a handcrafted feature extraction to classify and detect a given image as per its classes. The contribution of this work is twofold, using deep learning for potato disease detection and developing an AI-based android application prototype. An Image dataset that is labeled with three classes as 'Healthy', 'Early blight', and 'Late blight' is used as a benchmark. The pre-trained models of deep learning, MobileNet, and EfficientNet have shown 98% prediction performance. Finally, the model was built integrated with the android application and tested with unseen data.

Keywords: Convolutional Neural Network, Deep Learning, Potato Disease Detection, EfficientNet, MobileNet, Potato Leaf Disease

Introduction

Ethiopia's economic growth is stronger over the past decades. The major source of economic growth is the agriculture sector. It participates in 37 percent of GDP which is the highest percentage in the sub-Saharan countries and also contributes about 83.9 percent of exports. Additionally,

the sector employs around 72 percent of the total population (FAO, 2018). Despite a large number of agricultural products, the country remains dependent on imports of substantial amounts of semi-processed and processed food.

One of the highly consumed food items in Ethiopia is the potato, it serves as both cash and food security

crops. In the ruler area, about 68 percent of the total production was used for household consumption, and only 20 percent sold in the market. Furthermore, due to its nutrition, Ethiopia is considered a strategic commodity for ensuring food security (Zimmerman & J., 2015).

Potato is one of the crops, which is a faster-growing crop not only in Ethiopia but also in other sub-Saharan countries. The total area of land covered with potatoes has increased dramatically from 500,000 Mg to about 3,700,000 Mg in 10 years. The growth of potato production allows the country to achieve the food security program. Nonetheless, the productivity of the crop is low with an average yield of around 12.3 Mg/ha, the amount is very low compared to the attainable yields of 50 Mg/ha using improved farm management with improved varieties. The research identified Bacteria Wilt and Late Blight as the major potato production constraints and the number one disease that the farmers manage (Tafesse, et al., 2018).

Yitagesu Tadesse Demissie researched Ethiopian farmers' know-how about potato Late Blight disease that only a few farmers have information about potato's Late Blight disease (Demissie & Tadesse, 2019). This implies the need for technological solutions to support farmers and individuals who are investing in the agriculture sector. Furthermore, the problem has a great impact on developing countries because agriculture is the backbone of the economy and basic needs,

especially in Ethiopia where the mainstream of the population is a farmer.

Plant disease can cause social, economic, and ecological losses (Oberoi, Khan, & Ashish, 2019). Appropriate plant disease detection at an early stage prevents the devastation of the farm and the risk of food security of human beings. Some diseases are challenging to detect crop disease through naked eye observation. One of the challenges is the similarity of the diseases of the crop, in this case, to be sure of the exact disease of the crops requires a laboratory test by a plant pathologist. The problem challenged farmers and added effort on experts. Therefore, to overcome this problem researchers studied computer vision with machine learning and it achieved promising results. Currently, the state of the art technology uses deep learning which is a subset of machine learning, and achieved excellent results in plant disease detection using different parts of the plant.

Ethiopia has a good climate and soil cultivation for many different types of crops including potato, and it grows in different regions with various agro-economic conditions. Moreover, potato is one of the important cash crops, which gives ready cash to farmers. It is also known as 'complete food' as it contains carbohydrates, proteins, vitamin B, vitamin C, and minerals like phosphorus, calcium, and iron required for body growth. It is the richest source of starch, unlike other crops, it produces more food per unit

area with a short time (Demissie & Tadesse, 2019).

The production of potato crops is affected by *biotic* and *abiotic* factors. Among those, the major factor is the *biotic factor*, that caused by microorganisms like bacteria, fungus, and viruses. Many potato diseases affect the growth and production of the crop, to mention some of the diseases are *Early Blight*, *Late Blight*, *Septoria Leaf Spot*, and *Virus*. Besides, several factors affect potato yield, and that's called *abiotic factors*. To mention some, lack of well-performing cultivars, poor fruit setting due to heavy rains, and excessive-high temperature, and pests.

Late Blight disease is the major disease that affects potato farms of Ethiopian farmers compared to other potato diseases. Consequently, the yield per unit of potato is low relative to countries like Rwanda, Egypt, and Kenya. The disease is highly studied

and it is the most destructive one. It was responsible for a loss of \$5 billion annually and became a threat to food security (Demissie & Tadesse, 2019). Unless necessary management of the disease is taken, it could destroy 100% of the farm. Therefore, developing countries like Ethiopia need early detection of Late Blight disease, to save people's life and economy.

Artificial Intelligence (AI): refers to the simulation of human intelligence in computers designed to think and imitate humans' behavior. The term can also be applied to any system that shows characteristics linked to a human mind, such as learning and problem-solving. The concept of AI is based on the idea that human intelligence should be described in such a way that a computer can easily imitate it and perform tasks, from the easiest to the most complicated ones. Machine learning, deep learning, and CNN is a subset of AI. Figure 1 presents the AI and its subclasses.

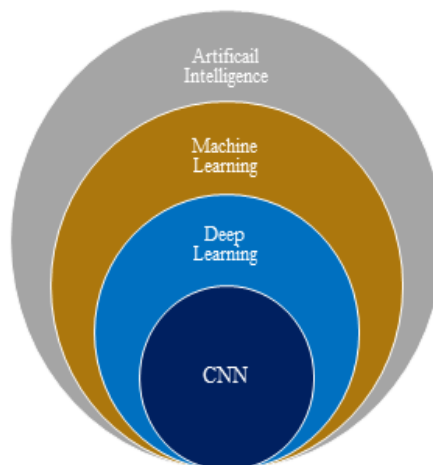


Figure 1: AI and its subclasses

Machine Learning: In classical programming, programmers feed data to the system with a rule, which applies to it, and finally based on this rule, the machine produces an output, which is an answer for a specific problem. However, some scholars began to ask a question like “could a computer go beyond what was ordered to perform?” and learn on its own how to perform a specified task? Could a computer surprise us? (Tyagi & Vipin, 2018). Those questions brought an opportunity to discover another programming paradigm called

Machine Learning. In this paradigm, programmers input data and answer, expecting *rules* as for output. These rules can be applied to the new data to provide the answer. Unlike classical programming, in machine learning the machine is trained rather than explicitly programmed. For example, to build an automating photo tagging system for vacation photos, a machine learning algorithm can be used. The machine learns a statistical rule by associating previous vacation photographs. Therefore, the vacation photograph is easily tagged.

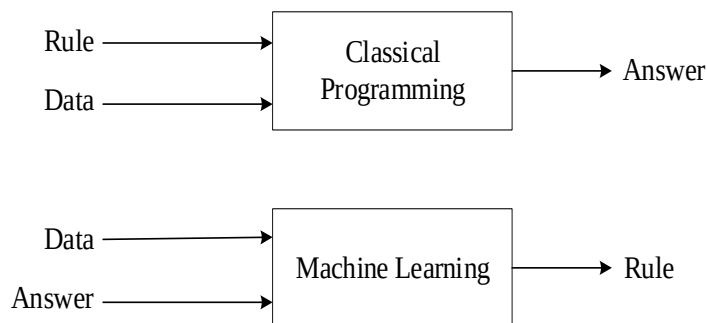


Figure 2: Classical programming vs Machine Learning

Deep learning: Deep Learning is a subfield of Artificial Intelligence (AI) that imitates the work of the human brain in the processing of data and the development of patterns for decision-making use. Deep learning is a subset of machine learning in AI that uses unlabeled or unstructured data as input to learning from it (Ashqar, Abu-nasser, & Abu-nasser, 2019).

Plant disease shows visual symptoms, which helps to classify and identify the disease affecting the crop that is used as an input for computer vision using a

deep CNN algorithm. D. Oppenheim et al. (Oppenheim, Shani, & Erlich, 2019) used CNN to classify potato tuber disease with five classes, the first class as healthy, and the other four were infected. The datasets collected have potato tubers with a variety of cultivars, size, and disease and also the image datasets labeled by plant pathologists. The dataset contains 400 images of disease-infected potato tubers having smooth skin with different color, shape, and captured using a standard camera under uncontrolled illumination. Captured

images labeled with Matlab 2014b software, and images transformed to grayscale with a dimension of 224x224 pixels. Before training the dataset a data augmentation was applied to increase the number of images, finally, a different experiment was conducted on the data partitioning of the dataset, the best result scored was 80-20 training and testing set data partitioning. The proposed CNN architecture is VGG and it has 8 learnable layers, the first five are convolutional layers followed by three fully connected layers, and finally, the end activation function used was Softmax, which helps to classify images into their classes and the model accuracy achieved was 95.8%.

M. Sardogan, A. Tuncer, and Y. Ozen used CNN and learning vector quantization (LVQ) for tomato leaf detection and classification, the dataset contains 500 images of the plant leaves under five classes, the first class is health tomato leaf and the other four class contain the plant's disease i.e. bacterial spot, Late Blight, Septoria Leaf spot, and yellow curved leaf disease (Sardogan, Tunc, & Ozen, 2018). Among the total dataset 400 images were used for training the model and 100 for testing the model. The source of the dataset is the PlantVillage repository (spMohanty, PlantVillage-Dataset, 2020) using this public benchmark dataset has limitations (Singh, et al., 2020) like the efficiency of the model when tested in a real-world image because of the real cultivation area heterogeneous and complex background. To train the

model CNN was used and for the data classification, LVQ has been used. LVQ is a powerful and heretic algorithm proposed by Kohonen and widely used for classification problems. It has three layers i.e. input layer, the Kohonen layer, and the output layer. The input layer and Kohonen layer are fully connected, while the Kohonen and output layer are partially connected. One of the challenges in (Sardogan, Tunc, & Ozen, 2018) was the uncanny similarity of some tomato leaf diseases, finally, the classification accuracy achieved was 86%.

H Durmu et al., experimented on plant disease detection using two deep learning architecture that is AlexNet and then SqueeZNet. Using Nvidia Jetson TX1 both models, the training and validation were done. The dataset has ten different classes including the healthy category. The trained models were tested with images from the internet. The authors compared the models using multiple metrics i.e. testing accuracy, model size, and inference time. Based on the comparison metrics of the two models finally, the SqueeZNet model was chosen for mobile deep learning classification because it is light and computationally efficient compared to AlexNet (Durmus, Gunes, & Kirci, 2017).

K. P. Ferentinos has developed a deep learning model called CNN to detect and classify potato disease by using their leaves. The potato plant's leaves

were sorted out as healthy and disease infected and a deep learning methodology was applied to it. To train a deep learning model the author used an open image database that contained 25 different plants in a set of 58 classes (Ferentinos, 2018). By experimenting with several deep learning model architectures one of the best achieved selected, which has 99.53% success.

Materials and Methods

Dataset

To detect Late Blight and Early Blight potato disease the required dataset is an image dataset that is a potato leaf image dataset, images of potato leaf collected from benchmark dataset (spMohanty, PlantVillage-Dataset, 2020), each picture of potato leaf captured by a high-resolution camera and the disease infected area is visible. The data collected sorted into three categories i.e. 'Healthy Potato Leaf', which has 152 images, 'Late Blight Infected Leaf', which has 1000 images, and 'Early Blight Infected leaf', which has 1000 amount of images. All the images' dimension is resized to 256*256 and the type of image is RGB. Furthermore, the benchmark dataset was preprocessed by experts to remove unnecessary features.

Data partitioning

The dataset is partitioned into training, and testing set. The training set is used to train the model to learn image features like curve, line, texture, and

other features. Finally, the test set is used after the model and hyperparameters are selected to measure the proposed model performance with unseen data. The total amount of data without partitioning is 2152 images, at first 85% of data used for the training set, which equals 1829 images per each class, 15% of the data is used for testing the model, which equals 323 images.

Model Training Tool

Many types of deep learning frameworks are available to implement deep learning to mention some of them *Theano*, *Keras*, *PyTorch*, *Teachable Machine*, and *TensorFlow*. There is no strict rule, which deep learning frameworks to use for implementing and solving problems of machine learning, however, the parameters that are efficient for the task are considered. Some of the parameters are the size of the dataset, availability of hardware components like GPU because AI research requires the high performance of the computer. During experimentation to train a neural network, Teachable Machine was used. The tool is an AI experimented by Google, which a web tool that makes it quick and simple, no coding is necessary, to build machine learning models for your projects. The tool can be used to recognize pictures, sounds, & poses after it is trained. Finally, the model export for your websites, android applications, and more. There are many advantages to using a

Teachable Machine. Some of the advantages are:

- It requires no top-performing hardware components like GPU.
- To train the neural network requires less effort compared to other API of deep learning
- The trained model easily exported and integrated with the website or android application
-

Model Evaluation

To evaluate how much a model is effective and performs well model evaluation is critical. A computational

problem like detection that predicts, which class instance belongs uses evaluation metrics accuracy, precision, recall, and F1-score. Those metrics calculated using the classification metrics. The classification metrics give an insight into the performance of a model for each class. All metrics mentioned above calculated based on the confusion matrix value i.e. TP(True Positive), TN(True Negative), FP(False Positive), FN(False Negative). The confusion matrix of the trained model is presented in Figure 5.

TN: Observation is positive and predicted to be positive.

TP: Observation is negative, and predicted to be negative.

FP: Observation negative, but predicted positive.

FN: Observation is positive, but predicted negative.

- Accuracy: Answers the question about how often the model predicts the classes correctly i.e. healthy leaf and disease infected leaf.
- Precision: It gives insight into how often a positive value prediction is correct. Example: Predicting image as a disease infected, how often the prediction precisely predicts.
- Recall: Also known as sensitivity it describes how sensitive the classifier is while detecting positive instances.
- F1-Score: Is the harmonic mean of the precision and recall, and the lowest value of F1-score is 0, which means one of the metrics has a value of 0. It indicates perfect precision or recall.

$$\bullet \text{ Accuracy} = \frac{TP+TN}{TP+FP+TN+FN}$$

Equation 1: Accuracy Metric

$$\bullet \text{ Precision} = \frac{TP}{TP+FP}$$

Equation 2: Precision Metric

$$\bullet \text{ Recall} = \frac{TP}{TP+FN}$$

Equation 3: Recall Metric

$$\bullet \quad F1 - Score = \frac{2}{\frac{1}{Recall} + \frac{1}{Precision}}$$

Equation 4: Recall Metric

Software tools

After the model was trained and exported in Tensorflow lite format, to integrate with an android application using Android Studio. The Android Studio was built based on JetBrains' IntelliJ Concept software and specifically developed for Android creation; Android Studio is the official integrated development environment for Google's Android operating system.

Algorithm

The deep learning algorithm (Convolutional neural network (ConvNets)), which has a wide application in computer vision was used. The algorithm is a widely used neural network to solve problems related to image classification, object detection, face recognition, image recognition, and others. The convolutional neural network is widely used in many applications to list some of them: image processing, image restoration, speech recognition, natural language processing, and bioinformatics. CNN is capable of detecting and classifying objects with minimal pre-processing, therefore it can achieve a high result to analyze objects, and also a separation of a feature with multilayered is easily done (Medium, 2020). The algorithm performs well on large amounts of data because as the data size increases during the training phase the neural network learns features that finally help to classify or recognize objects.

Since the amount of data used in the experiment is relatively less. To overcome this problem transfer learning was used. The next section explains transfer learning.

Transfer Learning

One of the most powerful ideas in deep learning is transfer learning, which a neural network is transfer learning, which is taught for a given task with data, and the knowledge generated would be transferred to another task (Ng, 2020). Formally transfer function is defined as Given a learning task T_t based on D_t and we can get help from D_s for the learning task T_s . Transfer learning aims to improve the performance of predictive function $f_T(.)$ for learning task T_t by discovery and transfer latent knowledge from D_s and T_s , where $D_s \neq D_t$ and /or $T_s \neq T_t$. Furthermore, in most cases, the size of D_s is much larger than the size of D_t , $N_s \gg N_t$ (Tan, et al., 2018). The trained model was exported to EfficientNet and MobileNet pretrained model formats, which are designed for running on mobile platforms because compared to other pretrained models it has the good processing power and memory with good speed after it converted to Tensorflow lite.

Results and Discussion

Using benchmark data as an input image with an RGB image format, which shows the Late Blight symptom

in detail experiment was conducted. Before integrating a model with the android application different parameters were tested to achieve the best result. Among several experiments, the trained model scored 98% accuracy in detecting Early Blight disease, 99% in detecting Late Blight Disease, and 96% in detecting the Healthy leaf. The best parameters, which scored the best score are epoch of 50, batch size of 16, and learning rate of 0.00002.

Figure 4 presents the accuracy trained model, at the beginning of the training,

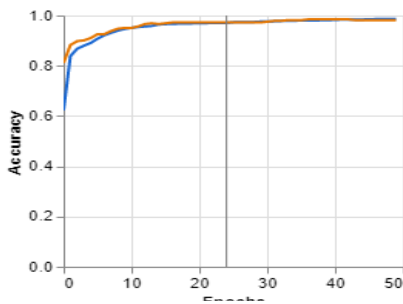


Figure 4: Training and testing accuracy

the model's accuracy i.e. training accuracy and the testing accuracy is low and gradually it increases the performance. Furthermore, in the figure, the training and testing accuracy of the model has no gap between them, this shows the model is not overfitted. Since the overfitted model has a problem during the testing phase. Figure 3 also has the same interpretation, because the loss of the training and testing is dropping and the graph has no gap between them.

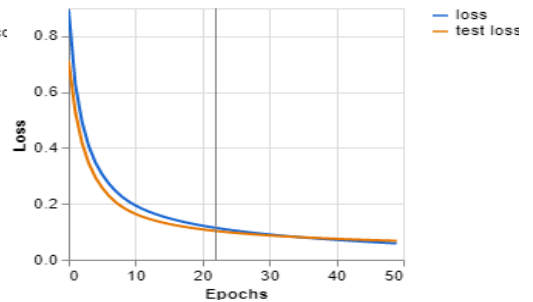


Figure 3: Training and testing loss

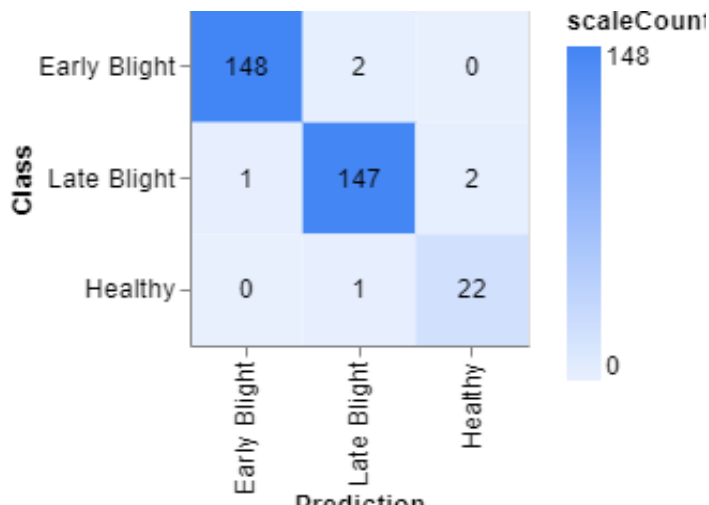


Figure 5: Confusion matrix of the model

Figure 5 presents the accuracy of the model per each class. It was interpreted as, in Early Blight class out of 150 images used for testing 148 images were detected correctly, and in Late Blight class out of 150 images used for

testing 148 were detected correctly, and finally in the Healthy class out of 23 images 22 images detected accurately by the model. The accuracy of the model for each class is summarized in Table 1.

Table 1: Accuracy per epoch

Accuracy per class		
Class	Accuracy	#samples
Early Blight	0.99	150
Late Blight	0.98	150
Healthy	0.96	23

Figure 6 presents the use case diagram of the potato’s leaf disease detector application. The diagram depicts the actors and interactions with the system. The actor is named ‘users’ because it is representative of the potential actors, the term includes actors like farmers, plant pathologists, and other individuals. There are three use cases in the figure, the major one is ‘ViewDiseaseType’. The use case

has a high relationship with ‘SelectModel’, and ‘SelectDevice’. In the ‘SelectModel’ use case, the users select the pretrained model from the Combo box, and the ‘SelectDevice’ use case gives the option to select hardware like CPU, GPU (Graphical Processing Unit), and NNAPI (Neural Network Application Program Interface).

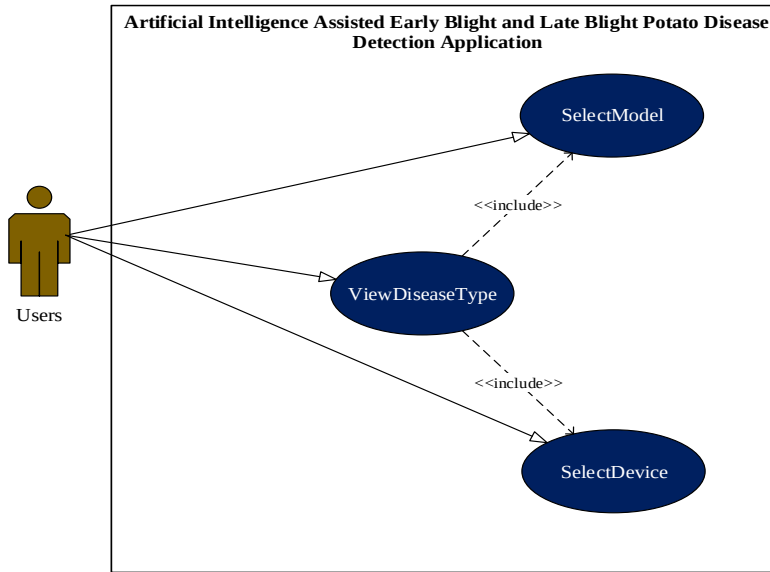


Figure 6: Use case diagram of potato disease detector application

Table 2 presents the detailed use case description of the application. The table description describes the end objective of the use case, actors, pre/post conditions, and flow between

the actors' actions and systems action. The use case description helps to understand the major use case and the activities performed in the use case.

Table 2: Use case description

Use Case ID: PROJ.AI.1.1		
Use Case Name:	View Disease Type	
End Objective:	To view the potato's disease (Late Blight, Early Blight)	
User/Actor:	Any user	
Pre-condition:	Users should open the application accordingly	
Post-condition:	Detecting the type of disease affected the crop	
Main flow:	Actors actions	System actions
	1. Users open the application. 3. User slide up the arrow displayed in #2 5. User click the labels combo box and select the model and /or devices	2. The application displays the home interface 4. The application displays the label 'Model' and 'Device' with a combo box. 6. The application's camera detects the type of disease in real-time 7. The confidence of disease with the label displayed 8. Use case ends.

The model was integrated with an android application using the Tensorflow Lite for android application. The steps help to detect the potato's disease is presented in Figure 7. As depicted in the figure the model predicts the Late Blight and Early Blight potato's leaf disease with high confidence.

Steps to use the potato plant disease detector application

The user interface of the application is simple and easy to use. Here steps to use the application are listed as follows.

Step 1: Open the disease detector application

Step 2: Slide the up arrow to view model and device Combobox

Step 3: Select the model to detect the potato's disease. Selecting the device type is optional.

Finally: The application camera becomes active and detects the disease in real-time showing the percent confidence, in which category the disease is found. Figure 7 shows the steps to use the application.

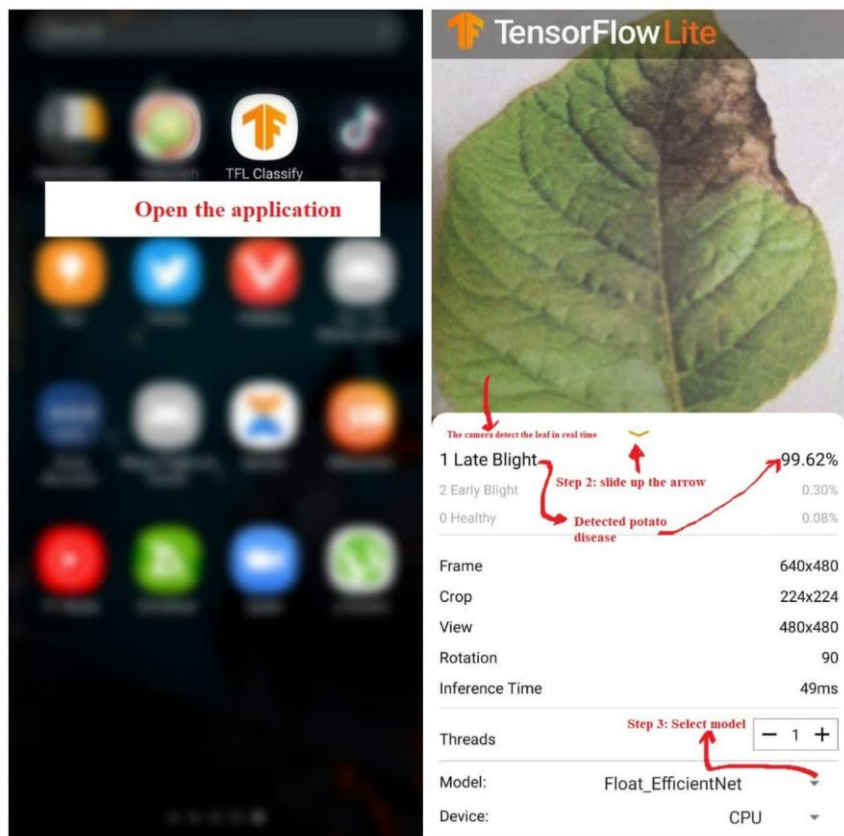


Figure 7: Steps to use the application

Conclusion and Recommendation

In this study, a potato disease detection android application was built which is capable of detecting the disease accurately. The diseases have the potential to destroy the whole potato field within a few days if there is ineffective management of the disease. The proposed model and application is capable of accurately detecting the Late Blight and Early Blight disease, which benefits not only the farmer but also maintains the country's food safety program. Having a sufficient amount of data the android application can be used for other several crop disease detection.

The crop potato was affected by several major diseases, and in this study, an AI-based android application was developed to detect the diseases 'Late Blight', and 'Early Blight'. To do so, computer vision with deep learning was used. Comparatively, a small dataset prepared and used, but it's better to collect and prepare a large local dataset based on the problem domain because the deep learning model becomes better at detecting the disease as the number of images increased, and also beside the leaf part of the potato crop including the fruit and steam parts help to completely detect and classify the crop's disease.

For farmers and others working in the agricultural sector, estimating the severity of the disease may be beneficial because it offers

information about how much the plant is affected by a disease and what course of action must be taken. This allows the sector to have accurate information about the stage of the disease, which simplifies the steps needed to be taken to handle the disease. Finally, in Ethiopia and other developing countries, the agricultural sector is the source of life and promises to ensure people's food security. Nevertheless, as per our observation, there are only a few studies conducted by scholars that combine artificial intelligence with the agricultural sector. Researchers should work together to change conventional farming practices by applying various technological solutions for a better outcome in the field.

Acknowledgment

This study is undertaken and inspired by MSc research at the Department of Software Engineering, under HPC and Big Data Analytics Center of Excellence. We would like to express our deepest appreciation for the direct or indirect involvement of all individuals in the process of completing this work.

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Genetic Variability and quantitative traits inheritance in Sesame (*Sesamum indicum* L.) Genotypes

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Abstract

Growing of low yielding and poor quality genotypes is among the major constraints of sesame production in Ethiopia. Field experiment was conducted to assess the extent of genetic variation and traits inheritance in sesame genotypes. A total of forty nine sesame genotypes were evaluated using simple lattice design at Bako and Uke during 2018 cropping season. The combined analysis of variance showed highly significant differences ($P < 0.01$) among the genotypes for all quantitative traits. Branches per plant, capsule per plant, biomass yield, harvest index, thousand seed weight and bacterial blight severity showed medium Phenotypic and Genotypic Coefficient of Variations. Seed yield, biomass yield, capsule per plant, bacterial blight severity and branches per plant showed moderately high heritability with high genetic advance as percent of mean. Thousand seed weight showed high heritability with moderate genetic advance as percent of mean. Harvest index showed medium heritability and genetic advance percent mean. Whereas, all the remaining traits showed medium heritability with low genetic advance as percent mean. Generally, this study depicted the presence of significant genetic variation among tested sesame genotypes and the possibility to get genetic progresses in the succeeding breeding generations.

Keywords: Genetic advance, Heritability, Sesame (*Sesamum indicum* L.), Variability

Introduction

Sesame (*Sesamum indicum* L.) is an annual plant of the *Pedaliaceae* family with diploid chromosomes ($2n = 26$) and considered as the oldest oilseed crop cultivated by man (Kafiriti and Deckers, 2001). It is a self-pollinated crop containing 60 species organized into 16 genera (Zhang *et al.*, 2013). It is commonly known with various names such as til (Hindi), huma

(Chinese), sesame (French), goma (Japanese), gergelim (Portuguese) and ajonjoli (Spanish) (Anilakumar *et al.*, 2010). Sesame originated in East Africa and India (Nayar and Mehra, 1970; Bedigian, 2003). It has been grown in the Near East and Africa for over 5,000 years for cooking and medicinal needs (Ekta *et al.*, 2014) but, recently it has been introduced into some American countries; viz., Mexico, Central America, South

America and U.S.A (Lalpantluangi and Shah, 2018).

In Ethiopia, the national average seed yield of sesame is 691 kg ha⁻¹ (CSA, 2018), which is quite low when compared to the yield potential of the crop (up to 2000 kg ha⁻¹) when grown at experimental stations (Mkamilo and Bedigian, 2007). An estimation of genetic variability is essential for understanding the genetic nature of yield and its components. Knowledge of heritability is essential for selection-based improvement, as it indicates the extent of transmissibility of a character into future generations (Sabesan *et al.*, 2009). Heritability can judge whether observed variability is heritable or non-heritable. Genetic advance measures the difference between the mean genotypic values of selected population and the original population from which these were selected.

Gadisa *et al.* (2015); Mohammed *et al.* (2015) and Desawi *et al.* (2017) reported the presence of genetic variability among sesame genotypes for days to flowering, days to maturity, plant height (cm), branches per plant, capsule per plant, biomass yield, seed yield, thousand seed weight (g), harvest index and oil contents traits.

Increasing yield is always a major aim in any plant breeding experiment. However, yield is the end product of action and interaction of vital activities of a plant throughout the life cycle and is controlled by numerous factors

shaped by genetics and environment. Therefore, assessing factors responsible for increasing yield is crucial issue. Improvement in plant breeding depends on variability, because superior genotypes cannot be selected from homogenous populations; but homogeneity is desirable in the final product of the crop variety. Hence, the present study was initiated to estimate variability, heritability and genetic advance in sesame genotypes.

Materials and Methods

Description of the study areas

The experiment was conducted at two locations; viz., Bako Agricultural Research Center (BARC) and Uke research subsite during the 2018 cropping season. BARC is located in East Wollega zone of Oromia Regional State at 250 kilometers West of Addis Ababa. BARC has a warm, humid climate with mean minimum and mean maximum temperatures of 13.97 °C and 29.80 °C, respectively. Relative humidity of BARC is 49.81% (BARC Agro metrology data, 2018).

Uke is located in East Wollega zone of Oromia Regional State, Guto Gida district at about 365 km away from Addis Ababa to the west and 34 km away from Nekemte town. The area is located at altitude of 1383 m.a.s.l. and it is an area with high temperature and abundant rainfall amount. Major crops produced in the area include: maize, sorghum, soybean, sesame and

groundnut. Some of the important agro-climatic and ecological

descriptions for both study areas are shown in Table 1.

Table 1. Description of the study area.

Site	Rain fall(mm)	Longitude (E)	Latitude (N)	Altitude (m.a.s.l.)	Soil type	Soil PH
Bako	1161.7	037° 09' E	09°06'N	1590	Sandy-clay	4.9- 5.1
Uke	NI	036° 31'E	09°22'N	1383	Sandy-loam	NA

NI = Not Available

Experimental materials

The experimental materials consisted of 46 genotypes (pure lines) and three checks (Waliin, Chalasa & Obsa) (Table 2). These genotypes are progenies of the intra-specific cross of 11 morphologically diverse sesame genotypes through continuous maintenance of progenies up to the seventh filial generation (F7) through selfing using F2-derived pedigree breeding method at Bako Agricultural

Research Center (Table 2). The original parent materials were collections from Western Ethiopia such as: EW002, EW003, BG006, EW023 (2), EW006, EW003 (1), EW019, EW010 (1), Obsa, Dicho and Wama. These eleven parent materials were crossed in a 11 x 11 diallel mating design, including reciprocals in the 2011 cropping season.

Table 2. List of sesame genotypes used for the study.

No.	Pedigree	No.	Pedigree
1.	EW002 X Obsa-1-1	26.	BG006 x EW023(2)-10-2-1
2.	EW002 X Obsa-16-1	27.	BG006 x EW010(1)-11-1-1
3.	EW002 X Obsa-22-1	28.	EW023(2) x Obsa-9-1-1
4.	Obsa x Dicho-19-1	29.	Obsa x BG006-2-2-1
5.	Obsa x Dicho-19-3	30.	Wama x Dicho-6-1-1
6.	Obsa x Dicho-27-1	31.	Obsa x EW023(2)-5-2-1
7.	EW002 x Dicho-1-1	32.	EW003(1) x EW002-4-1-1
8.	EW002 x Dicho-5-3	33.	Obsa x BG006-2-4-1
9.	EW002 x Dicho-12-1	34.	EW003 (1) x EW019-4-1-1
10.	EW002 x Dicho-17-2	35.	EW019 x Obsa-16-2-1
11.	EW002 x EW006-3-1	36.	EW003(1) x Obsa-2-1-1
12.	Dicho x EW006-9-1	37.	EW019 x Obsa-16-1-1
13.	Dicho x EW006-1-14-1	38.	Dicho x Wama-10-1-1
14.	BG006 x EW023(2)-11-2-1	39.	EW002 x EW019-1-2-1
15.	EW003 (1) x EW019-3-1-1	40.	EW019 x Dicho-8-2-1
16.	EW006 x EW003 (1)-4-1-1	41.	EW010(1) x EW003-1-1-1
17.	Dicho x EW006-2-1-1	42.	Obsa x EW019-6-3-1
18.	EW002 x BG006-4-1-1	43.	EW002 x Wama-6-1-1
19.	EW002 x BG006-7-2-1	44.	Dicho x Wama-11-1-1
20.	EW023(2) x EW006-11-1-1	45.	EW019 x Dicho-6-1-1
21.	EW002 x WAMA -2-1-1	46.	EW019 x Dicho-8-1-1
22.	Dicho x EW006-1-1-1	47.	Chalasa/EW023(2)(Parental check)
23.	EW006 x BG006-2-2-1	48.	Waliin (standard check)
24.	BG006 x EW010(1)-9-1-1	49.	Obsa (parental check)
25.	Obsa x EW023(2)-5-5-1		

Experimental design and trial managements

The trial was laid out using 7 x 7 simple lattice design. Each genotype was planted in 4 rows in plot size of 6.4 m² (4 m row length, 40 cm between rows and 10 cm between plants within row and spacing of 1 m between plots and 1.5 m between blocks). The seeds were drilled by hand in each row at the rate of five kg ha⁻¹ and then covered by soil. The plant depth and soil compactions were kept at a minimum. Twenty days after sowing, the plants were thinned to maintain the spacing between plants of 10 cm. Fertilizer was applied at the rate of 100 kg ha⁻¹ NPS at planting time. Whereas, 50 kg ha⁻¹ Urea was applied two times; at planting time and four weeks after planting. Other cultural practices were kept constant for all experimental units.

Data collection

All data were collected from the two central rows for both plant-based and plot-based data. Plant height, number of branches per plant, number of capsules per plant and bacterial blight severity (%) were collected from 10 randomly selected plants, but days to 50% flowering, days to maturity, biomass yield per plot, seed yield per

plot, thousand seed weight (g), harvest index (%) and oil content (%) were collected on plot bases. The data were collected according to the International Plant Genetic Resources Institute (IPGRI, 2004) descriptor for sesame.

Data analysis

The efficiency of a simple lattice design over RCBD was checked, and for most of the response variables, a simple lattice design was found to be more efficient than RCBD. Thus, ANOVA for quantitative analyses was computed based on a simple lattice design using Proc lattice and Proc GLM procedures of SAS version 9.3 (SAS, 2012). Homogeneity test for the error variance of the two locations was done using Hartley's test (1950) and checked by using F-test (ratio of the largest mean square error to the smallest mean square error in the set) according to Gomez and Gomez, (1984) and they were homogeneous. Hence, a combined analysis was computed.

Estimation of genetic parameters

The phenotypic and genotypic coefficients of variation were estimated according to the method suggested by Burton and Devane (1953) as follows:

Genotypic variance (δ_g^2)

$$\delta_g^2 = \frac{MS_g - MS_{gl}}{rl}, \text{ for over two locations;}$$

Where, MS_g = mean square of genotype,

MSgl is the mean square due to genotype by environment interaction,
 l = number of locations, and
 r = number of replications

Genotype by environment interaction variance (δ_{gl}^2)

$$\delta_{gl}^2 = \frac{MS_{gl} - MS_e}{r}$$

Where, MSgl is the mean square due to genotype by environment interaction, and
 MS_e = combined error mean square = (δ_e^2)

Phenotypic variance (δ_p^2)

$$\delta_p^2 = \delta_g^2 + (\delta_{gl}^2/l) + (\delta_e^2/r)$$

Where, δ_g^2 = genotypic variance, δ_{gl}^2 = genotypic by environmental variance, δ_e^2 = environmental variance, l = number of locations, and r = number of replications
 Estimates of coefficient of variation were obtained as follows.

Phenotypic coefficients of variation (PCV)

PCV = $\frac{\sqrt{\delta_p^2}}{\bar{X}} \times 100$; where, PCV = phenotypic coefficient of variation, δ_p^2 = phenotypic

Variance and $\bar{X}$ = population mean for the trait considered

Genotypic coefficients of variation (GCV)

GCV = $\frac{\sqrt{\delta_g^2}}{\bar{X}} \times 100$; where, GCV = genotypic coefficient of variation,
 δ_g^2 = genotypic variance, $\bar{X}$ = population mean for the trait considered

Environmental coefficients of variations (ECV)

$$ECV = \frac{\sqrt{\delta_e^2}}{\bar{X}} \times 100$$

Genotype by environment interaction coefficients of variation (GECV)

$$GECV = \frac{\sqrt{\delta_{gl}^2}}{\bar{X}} \times 100;$$

where, δ_{gl}^2 = genotypic x environment variance
 $\bar{X}$ = population mean for the trait considered

Estimation of heritability in broad sense

Broad sense heritability (H^2) expressed as the percentage of the ratio of the genotypic variance (σ_g^2) to the phenotypic variance (σ_p^2) and were estimated on genotype mean basis as described by Allard (1999):

$$H^2 = \left[\frac{\sigma_g^2}{\sigma_p^2} \right] * 100;$$

where, H^2 = broad sense heritability

$$\delta_g^2 = \text{genotypic variance}$$

$$\delta_p^2 = \text{phenotypic variance}$$

Estimation of genetic advance

Genetic advance in absolute unit (GA) and percent of the mean (GAM), assuming selection of superior 5% of the genotypes, were estimated in accordance with the methods illustrated by Johnson *et al.* (1955) as:

$$GA = k \sigma_p * H^2$$

$$GA \text{ (as \% of the mean)} = \left[\frac{GA}{\bar{X}} \right] \times 100;$$

where k = selection differential (k = 2.06 at 5% selection intensity)

σ_p = phenotypic standard deviation

H^2 = heritability (Broad sense)

$\bar{X}$ = Grand mean

Results and Discussion

Analysis of variance (ANOVA)

The pooled analysis of variance showed highly significant ($P < 0.01$) genotype effects across locations for days to 50% flowering, days to maturity, plant height (cm), branches per plant, capsules per plant, biomass yield per hectare (kg ha^{-1}), seed yield per hectare (kg ha^{-1}), harvest index (%), thousand seed weight (g), oil

content (%) and severity of bacterial blight (%), indicating the presence of considerable variation among the study genotypes (Table 3). Similarly, the variances for genotype by environment interactions were also highly significant for all traits except for biomass yield per hectare, harvest index and thousand seed weight ((Table 3). Supportive results were reported by Mohammed *et al.* (2015), Iqbal *et al.* (2018) and Singh *et al.* (2018).

Table 3. Mean square of combined analysis of variance for 11 traits of 49 Sesame genotypes evaluated at Bako and Uke in 2018 cropping season

Traits	MSI (Df=1)	MSg (Df=48)	MSgl (Df = 48)	MSe (Df = 84)	CV (%)	R ²
Days to Flowering	861.84**	27.22**	11.05**	2.15	2.34	0.94
Days to maturity	4585.22**	12.97**	5.36**	1.49	1.08	0.98
Plant height	38.88 ^{ns}	133.82**	71.81**	28.57	4.59	0.82
No. of branch/plant	22.22**	4.63**	1.78**	0.46	10.79	0.90
No capsule/plant	12542.40**	833.32**	288.06**	147.41	12.73	0.86
Biomass yield/ha	3259905.05**	1040847.35**	313201.83 ^{ns}	237629.93	14.09	0.80
seed yield/ha	400989.23**	218667.70**	60193.05**	33417.32	17.22	0.85
Harvest index	4.69 ^{ns}	60.31**	34.54*	19.34	14.38	0.76
1000 Seed weight (g)	12.13**	2.62**	0.88 ^{ns}	0.65	12.55	0.79
Oil content (%)	80.00**	2.27**	0.90**	0.18	0.77	0.94
Bacterial blight %	412.53**	47.36**	16.87**	5.29	12.09	0.90

Key: **, * and *ns* Indicate highly significance ($P < 0.01$), significant ($P < 0.05$) and not significance, respectively; MSI = Mean square of location, MSg = Mean square of genotype, MSgl = Mean square of genotype by location, MSe = Mean square of error, Df = degree freedom, CV= Coefficient of variation and R² = R square

Mean and Range Values

Mean and range for the 11 traits of 49 sesame genotypes are shown in Table 4. Days to 50% flowering ranged from 57.5 to 69.75, with a mean of 62.59. Days to maturity ranged from 108.25 to 12, with a mean of 112.87. The wider variability for days to flowering and maturity provides an opportunity to develop improved varieties for environments with a variable rainfall season or crop growing season. Plant height varied from 103.33 cm to 130.63 cm, with a mean of 116.48 cm. Number of branches per plant ranged from 4.40 to 8.93 with a mean of 6.31. Number of capsules per plant varied from 65.70 to 134.23 with a mean of 95.38, biomass yield ranged from 2232.90 to 4741.10 kg ha⁻¹ with a mean of 3458.99 kg ha⁻¹.

Seed yield per hectare ranged from 510.10 kg ha⁻¹ to 1694.20 kg ha⁻¹ with a mean yield of 1061.53 kg ha⁻¹, and harvest index ranged from 20.73% to 40.01% with a mean value of 30.58%. Thousand seed weight ranged from 5.09 g to 8.38 g with a mean value of 6.4 g and oil content ranged from 53.84 to 57.06 with a mean value of 55.52 and bacterial blight severity ranged from 11.33 to 26.00, with the mean of 19.03. This showed the wide range of variability for all tested traits of sesame genotypes used in the present study. Similar results were reported by Ahadu (2012), Begum and Dasgupta (2014), Mohammed *et al.* (2015), Desawi *et al.* (2014), Iqbal *et al.* (2016) and Begum *et al.* (2017).

Table 4. Estimation of mean, range and other genetic parameters of 49 sesame genotypes evaluated at Bako and Uke, 2018

Traits	Mean	Range		δ^2g	δ^2p	δ^2e	δ^2gl
		Minimum	Maximum				
Days to 50% Flowering	62.59	57.50	69.75	4.04	6.81	2.15	4.45
Days to 90% maturity	112.87	108.25	117.00	1.90	3.24	1.49	1.94
Plant height	116.48	103.33	130.63	15.50	33.46	28.58	21.62
No. of branch/plant	6.31	4.40	8.93	0.71	1.16	0.46	0.66
No capsule/plant	95.38	65.70	134.23	136.32	208.33	147.41	70.33
Biomass yield/ha	3458.99	2232.90	4741.10	181911	260212	237629.93	37785.95
seed yield/ha	1061.53	510.10	1694.20	39619	54667	33417.32	13387.87
Harvest index	30.58	20.73	40.01	6.44	15.08	19.34	7.60
1000 Seed weight (g)	6.40	5.09	8.38	0.43	0.66	0.65	0.12
Oil content (%)	55.52	53.84	57.08	0.34	0.57	0.18	0.36
Bacterial blight (%)	19.03	11.33	26.00	7.62	11.84	5.29	5.79

Key: δ^2g = genotypic variance, δ^2p = phenotypic variance, δ^2e = environmental variance, δ^2gl = genotypic by environmental interaction variance

Estimation of genetic parameters

Phenotypic variance (δ^2p), genotypic variance (δ^2g), environmental variance (δ^2e), genotype by environmental variance (δ^2gl) and their coefficients of variation were estimated and presented in Tables 4 and 5. According to Deshmukh *et al.* (1986), PCV and GCV values greater than 20% are regarded as high, while values less than 10% are considered to be low and values between 10% and 20% are medium. Phenotypic coefficients of variation (PCV) ranged from 22.03% for seed yield per hectare to 1.36% for oil content; and genotypic coefficients of variation (GCV) ranged from 18.75% for seed yield per hectare to 1.05% for oil content (Table 5). Therefore, seed yield in the present study showed relatively high PCV and medium GCV (Table 5). Medium PCV and GCV (10% up to 20%) were obtained for the number of branches per plant, number

of capsules per plant, biomass yield per hectare, harvest index, thousand seed weight and bacterial blight severity. The medium to high PCV and GCV value indicated that the variation observed among genotypes for these traits were due to their genetic difference rather than environmental influences. This showed effectiveness of simple selection based on these traits and their phenotypic expression would be a good indication of genetic potential.

Close relationship between phenotypic coefficients of variation (PCV) and genotypic coefficients of variation (GCV) were found in most of the traits considered in the current study. PCV values were slightly greater than GCV, revealing minor influence of environment for their expression. Similar result was reported by Thangavel *et al.* (2000). Low values (<10%) of PCV and GCV were obtained for days to 50% flowering, days to maturity, plant height (cm) and oil

content (%). Lower PCV and GCV suggested that the traits are rendering to the effects of high environmental influences and lower opportunity exists for improvement of these traits through simple selection. This result was correspondent with that reported by Mohammed *et al.* (2015). Additionally, Sumathi and Murlidharan (2010), Ahadu (2012), and Gidey *et al.* (2013) also reported low GCV and PCV values for days to 50% flowering, days to maturity and oil content.

Saxena and Bisen (2016) also reported low phenotypic and genotypic coefficients of variation for days to 50 per cent flowering and harvest index. Genotype by environmental coefficients of variation (GECV) ranged from 12.85% for branches per plant to 1.08% for oil content. Relatively the highest GECV were recorded for branches per plant (12.85%), bacterial blight severity (12.65%) and seed yield per hectare (10.9%). Environmental coefficients of variation (ECV) and genotype by

environmental coefficients of variation (GECV) were higher than genotypic coefficients of variation (GCV) for days to 50% flowering, days to maturity, plant height (cm), harvest index (%) and oil content (%).

This indicated that the phenotypic expression of these traits were highly influenced by environmental conditions rather than their genetic makeup; and hence improving these traits of interest would be effective based on a stability test that selection for such traits should be environmental-specific.

However, numbers of branches per plant, number of capsules per plant, seed yield per hectare, biomass yield per hectare, thousand seed weight (g) and bacterial blight severity showed that higher genotypic coefficients of variation (GCV) than genotypic by environment coefficients of variation (GECV). However, the high GCV recorded alone is not sufficient for the determination of the extent of genetic advance to be expected by selection.

Table 5. Estimation of genetic parameters for major morphological traits of 49 sesame genotypes evaluated at Bako and Uke, 2018

Traits	GCV	PCV	ECV	GECV	H ²	GA	GAM (%)
Days to 50% flowering	3.21	4.17	2.34	3.37	59.41	3.19	5.09
Days to 90% maturity	1.22	1.60	1.08	1.23	58.69	2.17	1.93
Plant height (cm)	3.38	4.97	4.59	3.99	46.34	5.51	4.73
No. of branch/plant	13.37	17.04	10.79	12.86	61.54	1.36	21.57
No capsule/plant	12.24	15.13	12.73	8.79	65.43	19.42	20.36
Biomass yield/ha	12.33	14.75	14.09	5.62	69.91	733.20	21.20
seed yield/ha	18.75	22.03	17.22	10.90	72.47	348.39	32.82
Harvest index (%)	8.30	12.70	14.38	9.01	42.73	3.41	11.16
1000 Seed weight (g)	10.30	12.65	12.55	5.39	66.29	1.10	17.24
Oil content (%)	1.05	1.36	0.77	1.08	60.31	0.93	1.68
Bacterial blight (%)	14.51	18.09	12.09	12.65	64.38	4.55	23.94

Key: GCV = genotypic coefficients of variation, PCV = phenotypic coefficients of variation, ECV = environmental coefficients of variation, GECV = genotypic by environmental coefficients of variation, H² = heritability, GA = genetic advance and GAM (%) = genetic advance as percent of mean

Estimation of broad-sense heritability and genetic advance

Heritability estimates provide information on the extent to which a particular genetic character can be transmitted to successive generations. According to Singh (2001), heritability values less than 40% are considered as low; heritability values between 40 to 59% are medium, heritability values between 60 to 79% are moderately high and heritability values $\geq 80\%$ are considered as very high. In this study, broad sense heritability ranged from 72.47% for seed yield per hectare to 42.73 % for harvest index (Table 5). Moderately high heritability values were obtained for seed yield (72.47%), biomass yield (69.91%), thousand seed weight (66.29 %), number of capsule per plant (65.43%), bacterial blight severity (64.38%), number of branches per plant (61.54%), oil content (60.31%) (Table 5). Such results indicated that the genetic makeup played a major role in the expression of these traits; and close correspondence between the genotypic and the phenotypic is due ultimately to less environmental influence on phenotypic expression of these traits, which is good for crop improvement through simple selection. Desawi *et al.* (2017) reported that moderately high heritability with high genetic advance mean for seed yield; and moderately high heritability with low genetic advance mean for oil content. Iqbal *et al.* (2016) and Begum *et al.* (2017) reported moderately high heritability

for thousand seed weight and seed yield, respectively.

Medium heritability values were observed for days to 50% flowering (59.41%), days to maturity (58.69%), plant height (46.34%) and harvest index (42.73%) (Table 5). Narayanan and Murugan (2013) reported medium heritability for days to 50% flowering (57.30%) and plant height (58.06%). Genetic progress expected from selection increases with an increase in genotypic variance. High heritability coupled with high genotypic coefficient of variation of the traits indicated that the traits respond effectively to phenotypic selection; hence, traits which had moderately high heritability coupled with medium genotypic coefficients of variation in the present study can be improved by conventional breeding through selection breeding. In general, genotypic coefficients of variation along with heritability estimate provide a reliable estimate of the amount of genetic advance to be expected through phenotypic expression. Medium heritability coupled with low genotypic coefficient of variation in the present study for days to 50% flowering, days to maturity, plant height and oil content indicated limited success in achieving genetic gain in the next breeding phases, if used as it is. Thus, direct selection for these traits will not be effective.

Falconer and Mackay (1996) classified genetic advance as percent of mean (GAM) values as low from 0 to 10%, medium/intermediate from 10 to 20%, and high $\geq 20\%$ values. Accordingly, GAM at 5% selection intensity was high for seed yield (32.82%), bacterial blight severity (23.94%), number of branches per plant (21.56%), biomass yield (21.2%) and number of capsules per plant (20.36%). Medium Genetic advance as percent of mean was obtained for thousand seed weight (17.24%) and harvest index (11.15%) (Table 5). The results indicated that these traits are governed by additive genes. Hence, simple selection based on those traits with high genetic advance as percent of mean will result in the improvement of the genotypes considered in this study. Gadisa *et al.* (2015) reported that high genetic advance as percent of mean was observed for number of branches per plant, number of capsules per plant, biomass yield, seed yield, harvest index, and thousand seed weight (g).

Low GAM was obtained for days to 50% flowering (5.092%), days to maturity (1.925%), plant height (4.731%), and oil content (1.68%) (Table 5). This showed that these traits are governed by non-additive genes, and thus simple selection, cannot be applied for the improvements of these traits. Generally, genetic advance as percent mean ranged from high (32.819%) for seed yield to low (1.681%) for oil content (%). The present study showed medium heritability and low genotypic

coefficients of variation as well as low genetic advance as percent of mean for days to 50% flowering, days to maturity, and plant height. On the contrary, high heritability, medium genotypic coefficients of variation (GCV) and a high genetic advance for plant height was reported by Begum *et al.* (2017). Besides, Thirumala *et al.* (2014) reported high heritability with high genetic advance as percent of mean for days to 50% flowering.

Medium genotypic coefficients of variation (GCV), with moderately high heritability and high genetic advance as percent of mean, were observed from number of branches per plant, number of capsule per plant, biomass yield per hectare, seed yield per hectare and bacterial blight severity. This result indicated that the phenotypic expression of these traits could be governed by the genes acting additively; and thus the importance of these traits through selection is reliable for the development of high yielding sesame genotypes. According to Johnson *et al.* (1955), high heritability estimates along with the high genetic advance is usually more helpful in predicting gain under selection than heritability estimates alone.

The present study showed that moderately high heritability coupled with high genetic advance as percent of mean was recorded for number of branches per plant, number of capsules per plant, biomass yield, seed yield, and bacterial blight severity. Ismaila and Usman (2014) reported high

heritability coupled with high genetic advance for number of capsules per plant, number of branches per plant, and yield per hectare, which indicated the additive nature of inheritance. However, a contrary result was reported by Mohammed *et al.* (2015) where high estimates of heritability coupled with medium genetic advance as a percent mean for oil content; and low heritability coupled with low genetic advance as percent of mean for number of branches per plant, number of capsules per plant, harvest index, and thousand seed weight in sesame genotypes.

According to Desawi *et al.* (2017), moderately high heritability with high genetic advance as a percent of mean was recorded for seed yield per hectare, and moderately high heritability with low genetic advance was observed for oil content. Generally, the high value for heritability and genetic advance of the traits considered in the present study provide information for the existence of wider genetic diversity among sesame genotypes, and this offers high chances for improving several traits of the crop through simple selection. Moreover, most of the traits considered in the present study recorded medium GCV and medium to moderately high heritability, and also exhibited high genetic advance reflecting the importance of additive gene effects in their inheritance and their expression. Hence, improving such traits through selection could be

efficient. Phunda and Narayanan (1993) reported that high values of genetic advance are indicative of additive gene action; whereas, low values are indicative of non-additive gene action.

Conclusions

The results of the study showed that there were high significant differences among tested genotypes for all traits indicating the presence of high variability for yield and other related traits in the studied genotypes, thereby indicating the possibility for further genetic analyses. Seed yield showed maximum PCV and moderate GCV. Moderately high heritability coupled with high genetic advance as percent of mean was recorded for number of branches per plant, number of capsules per plant, biomass yield, seed yield, and bacterial blight severity. This implied the possibility in achieving genetic gain in the next breeding phases. Generally, the present study showed existence of significant genetic variability among tested genotypes indicating the presence of a huge opportunity for further improvement through selection and other breeding approaches. Therefore, selection of promising genotypes could be possible to produce superior sesame varieties among the materials included in the present study.

Acknowledgements

This study was funded by Oromia Agricultural Research Institute Agricultural Growth Program (AGP-II). Bako Agricultural Research Center and team members of pulse and oil crops research are highly acknowledged for hosting the experiment and for assisted in field works, respectively.

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Trends in Observed Temperature and Rainfall Variability in Major Potato Growing Districts of Eastern Ethiopia

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Abstract

Potato (*Solanum tuberosum* L.) is a major cash crop in the eastern highlands of Ethiopia owing to the cooler and moist climate in the region. Climate variability threatens potato production since variations in rainfall patterns and temperature lead to severe moisture as well as other abiotic and biotic stresses for the crop. Therefore, we conducted a study to analyze trends in the variability of rainfall and temperature in three major potato growing districts (Woredas) in eastern Ethiopia, namely, Haramaya, Chiro, and Kombolcha. We acquired 38-year (1980–2017) historical and observed meteorological data from the National Meteorology Agency of Ethiopia. Trends of rainfall and temperature were analyzed using the Man-Kendall test. Rainfall variability analysis was done using the Precipitation Concentration Index (PCI), Standard Anomaly Index (SAI), and coefficient of variation (CV %). The results showed that, over the 38-year period, the annual amount of rainfall in Haramaya district varied by 17.8% while those of Kombolcha and Chiro varied by 66.8% and 28.7%, respectively. Both annual and seasonal maximum temperatures in Haramaya district showed significantly ($P < 0.05$) increasing trends whereas the maximum temperature in Chiro district showed a non-significantly increasing trend. The PCI value of Kombolcha ranged from high to very high indicating high concentration of rainfall in few months. Comparatively, Haramaya and Chiro districts experienced higher frequencies of drought than Kombolcha district. It is concluded that there was a significant increasing trend of minimum temperature at Haramaya and Chiro districts, and a significant increasing trend of Kiremt rainfall at Haramaya district that could lead to reduced potato yields and increased incidences of diseases. Therefore, options should be sought to tackle the variability in trends of temperature and rainfall and sustain potato production and enhance farmers' resilience to climate change.

Keywords: Annual rainfall; Annual temperature; Man-Kendall test; Precipitation Concentration Index (PCI); *Solanum tuberosum* L.; Standard Anomaly Index (SAI),

Introduction

Climatic variability plays an important role in agricultural production with a significant impact on crop growth, development, and yield, thus making the agricultural activity one of the most sensitive and vulnerable sectors among the anthropological activities (Ventrella *et al.*, 2012). Climate change-induced risks due to temperature variability, changes in rainfall pattern, and pest and disease outbreaks negatively influence agricultural production, productivity, and quality (Tesfahun, 2018). Long-term variability in rainfall and temperature is likely to increase the frequency of droughts and floods in Ethiopia (Amogne *et al.*, 2018). High rainfall variability in both temporal and spatial scale is a typical characteristic of climate in Ethiopia (Gissila *et al.*, 2004).

Precipitation is the key climatic variable that affects both the spatial and temporal patterns of water resources (Girma *et al.*, 2016; Xu *et al.*, 2018). Rainfall variability is directly related to the occurrence of flooding and drought (Li *et al.*, 2017). A study by FEWS NET (2012) indicated the declining rainfall and Belg crop production occurred along the eastern highlands of Ethiopia, stretching between the cities of Asebe Teferi (now Chiro) and Harar. In addition, recent observations (1990–2009) have indicated that this area no longer receives the average of 500 mm of rainfall during the March–June

season. Over the past decade, the average minimum and maximum temperatures of Ethiopia have increased by around 0.25°C and 0.1°C, respectively. Further, it is expected that in the year 2050, the mean temperature in the country will increase by 1.7–2.1°C (Tadege, 2007).

Knowledge and technology are required for adaptation to climate change, seasonal climate prediction, and land productivity management (FAO, 2007). Previous studies revealed inconsistent results in annual and seasonal rainfall trends (Gebre, 2014) and rainfall and temperature patterns showed large regional differences (Zerga and Gebeyehu, 2016). Therefore, investigations into climate change trends at local levels is recommended because large-scale studies of climate change scenarios that focus on large areas would be of little use for local agriculture, particularly in places where rainfall is highly variable and geophysical characteristics vary within short distances. Besides, local level climate change trend analysis is vital for context-specific planning and implementation of adaptation interventions (Gebre *et al.*, 2013; Aragaw and Woldeamlak, 2017).

Potato is highly vulnerable to climate variability (Aniek *et al.*, 2013). The main climatic factors that can greatly influence the growth and development of potatoes are air temperature, rainfall, and light (Fleisher *et al.*, 2017). The yield and total profit from potato are affected by unpredictable

variability in rainfall patterns, changes in temperature, precipitation, and unusual storms (Fleisher *et al.*, 2017). Fluctuations in quantity and quality of potato yields have been also caused by increasing temperatures, drought and floods, post-harvest losses, increasing costs of replanting and production, increasing pest and disease incidences, as well as increasing soil erosion (Jovovic *et al.*, 2016).

The eastern highlands of Ethiopia are characterized by high population density, small land size, declining soil fertility, rugged topography, severe land degradation, fragile ecosystems (Tesfaye and Seifu, 2016) and recurrent weather-induced shocks such as drought. As a result, the region is among the most chronically food-insecure areas of the country (Mulugeta *et al.*, 2018). In this connection, potato producing smallholder farmers in eastern Ethiopia face frequent risks of disease outbreaks, pest damage, post-harvest losses, and occurrence of extreme weather events (Sisay *et al.*, 2019). Therefore, understanding the magnitude and trend of variability of climate variables and documenting the influence of climate variability on specific crops in major production areas could provide useful information for early warning and suitable adaptation options. However, to understand and document the change in climate, specific causes of potato crop failures that are related to rainfall and temperature variability have not been elucidated in the area. Therefore,

this paper presents research results on trends in rainfall and temperature variability that affect potato production in major areas growing the crop in the eastern highlands of Ethiopia.

Methodology

Description of the study areas

The study was conducted in three major potato growing districts in eastern Ethiopia. They are Haramaya and Kombolcha districts in the East Hararghe Zone and Chiro district in the West Hararghe Zone. Haramaya is located at 42°3'E longitude, 9°26'N latitude, and at a mean altitude of 2006 meters above sea level, which puts the area into the category of a highland. Haramaya district (*Woreda*) has the altitude ranging from 1400 to 2340 meters above sea level. It is situated in the semi-arid tropical belt of eastern Ethiopia. The mean annual rainfall received in the district ranges from 600 to 1260 mm. The rainfall is bimodal. The district is representative of a sub-humid mid-altitude agro-climatic zone. The short rainy season usually starts in March and ends in May, and the long rainy season (*Ganna or Kiremt*) occurs between June and September. The relative humidity varies between 60 and 80%. The minimum and maximum annual temperatures range from 6°C to 12°C and 17°C to 25°C, respectively (Nigussie *et al.*, 2014). Kombolcha district is situated between 09°22' N–09°35' N and 42°06' E–42°13' E with the altitude that ranges from 1200 to

2460 meters above sea level (Nigussie *et al.*, 2014; Nigussie *et al.*, 2018). The short rainy season usually starts in March and ends in May, and the long rainy season rainfall occur between June and September. Chiro district has latitude and longitude of 09°05' N 40°52' E/ 09°083'N 40°867' E. The altitude of the area ranges between 1826–1950 meters above sea level. The mean annual rainfall received in the district was 927 mm. The minimum and maximum annual temperatures were 27.87°C and 12.72°C, respectively.

Climate variability analysis

Climate data including daily rainfall (RF) and temperature (T-max and T-min) of 38 years for Haramaya, Kombolcha, and Chiro were obtained from the National Meteorological Agency (NMA) of Ethiopia. Before analysis, the data were scanned for missing values. The World Meteorological Organization recommends 30 years as the minimum duration for data required to search evidence of climatic change in hydro-climatic time series (IPCC-GCIA, 1999). Therefore, the maximum flexible threshold of 10% missing value adopted by Ngongondo *et al.* (2011) was considered in this study. To reconstruct the gap and fill the missing values, data were generated using the weatherman database in the DSSAT version 4.7. Then, the generated data were checked for physical representativeness of the respective sites. INSTAT + version 3.36) (Stern *et al.*, 2006) was used to

summarize the daily data into annual, monthly, and seasonal totals and to analyze the onset and cessation of the rainy season and length of the growing period (LGP).

Data quality control

Outlier detection: identification of outliers (suspicious data) has been the primary emphasis on the climatic database development (Gonzalez – Rouco *et al.*, 2001). Outliers are values greater than a threshold value of a specific time-series data that can affect the detection of in homogeneity (Gonzalez-Hidalgo *et al.*, 2009). For non- normally distributed data like rainfall, the Tukey fence is recommended for trimming the outlier (Ngongondo *et al.*, 2011):

$$[Q_1 - 1.5 \times IQR, Q_3 + 1.5 \times IQR]$$

Where Q1 and Q3 are, respectively, the lower and upper quartile points, 1.5 is a standard deviation from the mean, and IQR is the inter quartile range. Values outside the Tukey fence are considered as outliers. In this study, such outliers were set to a limit value corresponding to $\pm 1.5 \times IQR$.

Homogeneity test: the second step of the quality control process was the analysis of homogeneity.

In this particular study, due to its lower demands in application and interpretation, a cumulative deviation test was used for absolute testing (using stations own data). This method is commonly used in climatology to detect in homogeneities in the meteorological time series

(Ngongondo *et al.*, 2011; Kang and Yusof, 2012). Buishand (1982) noted that tests for homogeneity can be based on the adjusted partial sums or cumulative deviations from the mean and it is given as follows:

$$S^*_0=0 \text{ and } S^*_K = \sum_{i=1}^K (y_i - \bar{y}), \quad K=1 \dots n$$

The term S^*_K is the partial sum of the given series. If there is no significant change in the mean, the difference between y_i and $\bar{y}$ will fluctuate around zero. The significance of the change in the mean was calculated with 'rescaled adjusted range' R , which is the difference between the maximum and the minimum of the S^*_K values scaled by the sample standard deviation is:

$$R = (\max_{0 \leq k \leq n} S^*_K - \min_{0 \leq k \leq n} S^*_K) / SD$$

Then the critical value for $R/\sqrt{n}$ was calculated by Buishand (1982) and for $n=30$ its value is 1.5 and 1.4, respectively, for 5% and 10% probability levels.

Test of randomness and persistence: It is well known that the time series data required for trend analysis should be random and/or non-persistent (Ngongondo *et al.*, 2011). Before proceeding to trend analysis, the time series data was tested for randomness and independence using the autocorrelation function (r_1) as described in Box and Jenkins (1976) in the following manner.

$$r_1 = \frac{\sum_{i=1}^{n-1} (x_i - \bar{x})(x_{i+1} - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

Where x_i is an observation, x_{i+1} is the following observation, $\bar{x}$ is the mean of the time series, and n is the number of data. Also, Dahmen and Hall (1989) defined the critical region at 5% probability as follows;

$$\left[(-1 - 1.96\sqrt{(n-2)})/(n-1), \quad (-1 + 1.96\sqrt{(n-2)})/(n-1) \right]$$

For the study serial correlation of lag-1 (the correlation of two consecutive observations in the time series data) was employed. Whenever a significant correlation appeared in the data series, the data series was 'pre-whitened' following the procedure described by Patal and Kahya (2006). The pre-whitened data series was obtained as:

$$(X_2 - r_1 X_1, X_3 - r_1 X_2, \dots, X_n - r_1 X_{n-1})$$

Variability Analysis

Analysis of standardized anomaly index, rainfall/precipitation concentration index (PCI), and coefficient of variation were used as descriptors of rainfall variability (Bewket and Conway, 2007; Ayalew *et al.*, 2012).

Standardized Anomaly Index (SAI)

was calculated as the difference between the annual total of a particular year and the long-term average rainfall records divided by the standard deviation of the long term data. This index was used to examine the nature of the trends and enable to determine the dry and wet years in the record. The choice of the index is justified by its capacity to rapidly detect situations of drought and assess its acuteness. It is also highly recommended by climatologists because it is less complex than many other drought indexes (Tossou *et al.*, 2017). It is calculated as:

$$RA_{ij} = \frac{P_t - P_m}{\delta}$$

Where, RA_{ij} is normalized rainfall total for station i during a year (or season) j ; P_t is the annual rainfall in year t ; P_m is long term mean annual rainfall throughout observation; and δ is the standard deviation of annual rainfall throughout the observation. Positive normalized rainfall anomalies indicate greater than long-term mean rainfall, while negative anomalies indicate less than the mean rainfall. When averaged over several stations, the normalized rainfall anomaly yields

a normalized rainfall anomaly index. Drought severity classes include extreme drought ($SAI < -1.65$), severe drought ($-1.28 > SAI$), moderate drought ($-0.84 > SAI > -1.28$), and no drought ($SAI > -0.84$) (Dereje *et al.*, 2012).

Precipitation concentration index

(PCI) was used for characterizing the monthly rainfall distribution and was analyzed using the formula described by De Luis *et al.* (1999) as:

$$PCI = 100 \times \left[\sum_{i=1}^{12} P_i^2 / \left(\sum_{i=1}^{12} P_i \right)^2 \right]$$

Where, P_i is the rainfall amount of the i^{th} month. According to Oliver (1980), PCI values can be categorized ranging from a uniform distribution (low) to a strong irregular distribution (very high) (Table 2). An inter-annual fluctuation was evaluated by calculating standardized rainfall anomalies and graphically presenting the results. Precipitation Concentration Index (PCI) values categorized as $PCI < 10$ (uniform rainfall distribution (low rainfall concentration), $10 < PCI \leq 15$ (moderate rainfall distribution), $16 < PCI < 20$ (irregular distribution (high concentration), and $PCI > 20$ (strong irregularity (very high concentration) (Oliver, 1980). For climate variability, the precipitation concentration index (PCI) is a powerful indicator of the temporal distribution of precipitation on the annual scale and seasonal scale in different parts of the world. This method is recommended as it can provide information on long-term total

variability in the amount of rainfall received for a given area (Oliver, 1980).

For this study, precipitation concentration index (PCI) is analyzed. The PCI allows quantifying the relative distribution of precipitation patterns. Many scholars divided seasons into four but in this study, the season was divided into three. And also, unlike most of the tropics where two seasons are common (one wet season and one dry season), three seasons are known in Ethiopia, namely 'Bega' (dry season) which extends from October- January, 'Belg' (Short rain season) which extends from (February- May), and 'Kiremt' (long rainy season) which extends from June- September (NMSA, 2007). The PCI was calculated on a seasonal scale for Belg, Kiremt, and Bega.

$$PCI = 33.333 \times \left[\sum_{i=1}^4 P_i^2 / (\sum_{i=1}^4 P_i)^2 \right]$$

The coefficient of variation (CV): it was calculated to evaluate the variability of the rainfall and its characteristics by dividing the standard deviation of the event to its mean. In this study, the coefficient of variation (CV) was calculated to evaluate the variability for each year of the rainfall and its characteristics. A higher value of CV is the indicator of larger variability, and vice versa which is computed as:

$$CV = \frac{\sigma}{\mu} \times 100$$

Where CV is the coefficient of variation; σ is the standard deviation and μ is the mean precipitation. According to Hare (2003), the degree of variability of rainfall events was classified as less ($CV < 20\%$), moderate ($20\% < CV < 30\%$), and high ($CV > 30\%$). However; according to (Hadgu *et al.*, 2013) the CV has been classified as low variability ($CV < 20\%$), moderate rainfall variability (between 20% and 30%), high variability ($CV > 30\%$), very high ($CV > 40\%$) and extremely high inter-annual ($CV > 70\%$) variability; hence this study used the scales used in this category.

Determination of trends in annual and seasonal rainfall and temperature

In this study, the Mann–Kendall trend test was employed. Mann–Kendall trend test is a non-parametric method which is less sensitive to outliers and test for a trend in time series without specifying whether the trend is linear or non-linear (Partal and Kahya, 2006; Yenigun *et al.*, 2008). World Meteorological Organization (WMO) recommends the non-parametric Mann–Kendall (MK) test statistic for the assessment of trends in meteorological data (Ngongodo, 2011).

The data values are evaluated as an ordered time series. Each data value is compared to all subsequent data values. The initial value of the Mann–Kendall statistic, S , is assumed to be 0 (*e.g.*, no trend). If a data value from a

later period is higher than a data value from an earlier

period, S is incremented by 1. On the other hand, if the data value from a later period is lower than a data value sampled earlier, S is decremented by 1. The net result of all such increments and decrements yields the final value of S .

Let $x_1, x_2, \dots, x_n$ represents n data points where j represents the data point at time j . Then the Mann-Kendall's test statistic is given as:

$$S = \sum_{i=1}^{N-1} \sum_{j=i+1}^N \text{sgn}(x_j - x_i)$$

Where S is the Mann-Kendal's test statistics; x_i and x_j are the sequential data values of the time series in the years i and j ($j > i$) and N is the length of the time series. A positive S value indicates an increasing trend and a negative value indicates a decreasing trend in the data series.

The sign function is given as

$$\text{sgn}(x_j - x_i) = \begin{cases} +1 & \text{if } (x_j - x_i) > 0 \\ 0 & \text{if } (x_j - x_i) = 0 \\ -1 & \text{if } (x_j - x_i) < 0 \end{cases}$$

A very high positive value of S is an indicator of an increasing trend, and a very low negative value indicates a decreasing trend. However, it is necessary to compute the probability associated with S and the sample size, n , to statistically quantify the significance of the trend.

The variance of S , for the situation where there may be ties (i.e., equal values) in the x values, is given by

$$\text{Var}(S) = \frac{1}{18} \left[N(N-1)(2N+5) - \sum_{i=1}^m t_i(t_i-1) \right]$$

Where: m is the number of tied groups in the data set and t_i is the number of data points in the i^{th} tied group. For n larger than 10, Z_{MK} approximates the standard normal distribution (Partal and Kahya, 2006; Yenigun *et al.*, 2008) and computed as:

$$Z_{MK} = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0 \end{cases}$$

The presence of a statistically significant trend was evaluated using the Z_{MK} value. In a two-sided test for trend, the null hypothesis H_0 should be accepted if $|Z_{MK}| < Z_{1-\frac{\alpha}{2}}$ at a given level of significance. $Z_{1-\frac{\alpha}{2}}$ is the critical value of

Z_{MK} from the standard normal table. E.g. for a 5% significance level, the value of $Z_{1-\frac{\alpha}{2}}$ is 1.96. Z implies the significance of

the trend analyzed in the study if Z calculated is greater than Z tabulated (1.96) and (2.57) considered as significant at 5% and 1%; respectively. However, if Z calculated is greater than Z tabulated (1.64) considered as significant at 10%.

The Sen's estimator of slope: This test is applied in cases where the trend is assumed to be linear, depicting the quantification of changes per unit time. The slope (change per unit time) was estimated following the procedure of Sen (1968). A detailed outline of the procedure is given in Partal and Kahya (2006); and Karpouzou *et al.* (2010).

Table 1. Baseline period, weather variables and geographical locations of the study areas

Location	Altitude (m.a.s.l.)	Latitude (°N)	Longitude (°E)	Baseline period	Years with Missing values/No. of years with missing values	Weather variable
Haramaya	2020	9.40	42.0333	1980-2017	1993-1996	RF, T-max, T-min
Kombolcha	2122	9.4333	42.1167	1980-2017	1992,1993,2016,2017	RF
Chiro	1792	9.0725	40.8715	1980-2017	1991,1992	RF, T-max, T-min

Key: *m.a.s.l. = meters above sea level; RF = rainfall; Tmax = maximum Temperature; Tmin = minimum temperature.

Results and Discussion

Analysis of Climate Variables

Coefficient of the variability of temperature and rainfall

The total amount of annual rainfall for Haramaya district was low in coefficient of variability (CV). However, Chiro and Kombolcha districts had moderate and high CV values, respectively (Table 2). This result implies that variability was higher in the latter two stations than the former one. Unlike the coefficient of variability in the total annual rainfall, the coefficient of variability in the amount of *Kiremt* or *Ganna* rainfall for Haramaya district was moderate. However, Kombolcha district showed high variability for both seasonal and annual rainfall amounts (Table 2). This indicates the existence of high intra-annual variability. The annual rainfall variability of Haramaya was low (Table 4).

Seasonal variability was found for all of the study areas with varying magnitude. The seasonal rainfall variability for all of the study districts indicated that the *Belg* season rainfall was more variable than the *Kiremt* season rainfall. This inter- and intra-annual variability could have an impact on productivity of the potato crop. Consistent with this result, Amogne *et al.* (2018) reported a higher CV value for *Belg* rainfall than

for *Kiremt* rainfall. This result also agrees with the findings of Seleshi and Zanke (2004), Bewket and Conway (2007), Hadgu *et al.* (2013), who reported that the variability in *Belg* season rainfall was higher than that in *Kiremt* season rainfall.

In this study, the mean contribution of *Belg* rainfall to the total amounts of rainfall in Haramaya and Chiro districts was found to be about 35%. Likewise, the mean contribution of *Kiremt* rainfall to the total rain that fell in the two districts was on average about 53%. On the other hand, the contribution of *Belg* rainfall to the total amount of rain that fell in Kombolcha district was relatively high, which was above 40% (Table 2). This indicates that the areas have close similarity in spatial rainfall patterns which makes them potential areas for potato production. Furthermore, the data revealed that Kombolcha district had a more favorable rainfall pattern for double cropping the potato crop than the other two districts given the relatively higher amount of rainfall it receives compared to the other two districts.

Table 2. Mean standard deviation (SD), coefficient of variation (CV) and percentage proportion of seasonal and annual rainfall amount for three locations in eastern Ethiopia for the baseline years 1980–2017

Season	Haramaya				Chiro				Kombolcha			
	Mean rainfall (mm)	Seasonal contribution (%)	SD	CV (%)	Mean rainfall (mm)	Seasonal contribution (%)	SD	CV (%)	Mean rainfall (mm)	Seasonal contribution (%)	SD	CV (%)
Belg (FMAM)	274.70	34.60	104.14	37.92	328.77	36.26	161.71	49.18	430.52	43.24	472.36	109.72
Bega (ONDJ)	82.80	10.43	68.48	34.60	108.98	12.02	108.29	99.36	86.14	8.65	90.08	104.57
Kiremt (JJAS)	436.30	54.97	87.39	20.03	468.93	51.72	154.46	32.94	478.98	48.11	215.89	45.07
Annual	793.70	100.00	141.23	17.8	906.68	100	260.33	28.71	995.65	100	665.55	66.84

Key: 'Kiremt' means main rainy season; 'Bega' means dry season; 'Belg' means short rainy season; FMAM = February, March, April, and May; ONDJ = October, November, December, January; JJAS= June, July, August, September

The mean main (*Kiremt*) season rainfall for Haramaya was 436.3 mm, that for Chiro was 468.93 mm, and that for Kombolcha was 478.98 mm (Table 2). The potato plant is not resistant to drought but requires only moderate rainfall or equivalent irrigation, which is uniformly distributed throughout the growing season. The crop is most sensitive to water stress during tuber initiation and bulking (Devaux and Haverkort, 1987). Accordingly, the study areas receive optimum mean annual rainfall for potato production. This indicates that the total amount of rainfall received in the districts is moderate and sufficient for potato production.

In contrast to the *Belg* rainfall, the Man-Kendall test result of this study revealed a significantly increasing trend in *Kiremt* rainfall for Haramaya. However, the variability in the amount and any erratic distribution of the rainfall would have significant negative impacts on potato production. This suggestion is consistent with that of Girma *et al.* (2016) and Xu *et al.* (2018) who indicated that precipitation is the key climatic variable that affects both the spatial and temporal patterns of water resources. On the other hand,

the increment in *Kiremt* rainfall could create unfavorable condition for potato production by enhancing incidences of diseases particularly potato Late Blight disease caused by *Phytophthora infestans* (Mont) de Bary. Consistent with this suggestion, Olanya *et al.* (2006) reported that Late Blight disease of potato became a serious problem in potato production especially under high rainfall condition. In particular, the potato plant is most sensitive to water stress during tuber initiation and bulking. This suggestion is consistent with that of Devaux and Haverkort (1987), Loon van (1981), and Haverkort (1990) that too much rainfall and high humidity predisposes the potato plant to various fungal and bacterial diseases. Therefore, farmers should practice control measures against the disease to produce the crop under intense amounts of rainfall occurring as a result of climate variability. On the other hand, the increasing trend in *Kiremt* (main season rainfall) rainfall in the districts studied could be seized as an opportunity to use water harvesting technologies for enhancing production of the crop.

Table 3. Mean standard deviation and coefficient of variation of seasonal and annual temperature variability in Haramaya and Chiro districts for the baseline years of 1980–2017

Variable	Season	Location					
		Haramaya			Chiro		
		Mean	SD	CV (%)	Mean	SD	CV (%)
Maximum temperature (°C)	<i>Belg</i>	25.10	0.67	2.60	28.23	1.05	3.74
	<i>Bega</i>	23.21	0.45	1.90	27.12	1.11	4.09
	<i>Kiremt</i>	23.84	0.57	2.40	28.11	1.04	3.70
	Annual	24.05	0.45	1.88	27.82	0.92	3.30
Minimum temperature (°C)	<i>Belg</i>	10.74	1.13	10.53	13.70	2.19	16.02
	<i>Bega</i>	5.10	1.50	29.47	12.17	1.79	14.73
	<i>Kiremt</i>	13.39	0.96	7.19	14.30	0.51	14.36
	Annual	9.74	0.90	9.25	13.39	1.88	14.03
Mean temperature (°C)	<i>Belg</i>	17.92	0.66	3.67	20.97	1.30	6.19
	<i>Bega</i>	14.15	0.75	5.31	19.65	0.96	4.90
	<i>Kiremt</i>	18.61	0.68	3.67	21.21	0.96	4.54
	Annual	16.90	0.57	3.36	20.61	0.94	4.57

The optimum temperature for potato production ranges between 18 to 30 °C (Hijman, 2003; Muthoni and Kabira, 2015). However, the CV of the minimum temperature for Haramaya showed high variability for *Bega* (dry) season. However, the other seasons (*Kiremt* and *Belg*), showed low variability (Table 3). On the other hand, the CV for *Chiro* revealed that both annual and seasonal minimum temperatures had moderate variability. Temperature variability could influence tuber initiation and bulking of potato. Higher temperatures have adverse effects on metabolic activities and increase evapo-transpiration from the plant. Rising temperatures also accelerate plant development and leaf senescence. Higher temperatures during tuber bulking reduce translocation of carbohydrates from other plant part to the tubers (CIPC, 2007). If the temperature is higher

than 30°C, the crop will not tuberize and grows mainly vegetatively. Potato yields decrease in many regions especially in the tropics because of increasing temperatures. All potato varieties do well in cool climate between 15°C to 18°C, and temperatures beyond 20°C shorten the growing period, thereby reducing assimilate accumulation and ultimate yields obtained from the crop (Hijman, 2003).

Precipitation concentration index (PCI)

Chiro and Kombolcha districts had high concentrations of inter-annual variability (PCI >16%) (Table 4). This implies an irregular distribution of rainfall (poor monthly distribution). It means the degree of seasonality in the specified area is high. Correspondingly, the mean annual PCI value in case of Haramaya district was

in the moderate and high categories (15.81%). Compared to that of Haramaya and Chiro districts, the inter-annual variability of Kombolcha was very high. This irregular distribution of annual rainfall could affect production of potato across years. *Kiremt* season rainfall distribution for Haramaya and Chiro was uniform whereas it was moderate for Kombolcha, indicating seasonality. Conversely, *Belg* season rainfall for Haramaya showed irregularity which

could have impact on the growth and development of potato, which may create difficulty in implementing and maintaining the previously used optimal planned farming operations. These results are consistent with seasonal rainfall trends observed by Gebre (2014) and rainfall and temperature patterns that showed large regional differences in Ethiopia as reported by Zerga and Gebeyehu (2016).

Table 4 Annual and seasonal Precipitation Concentration Index (PCI) and percent proportion of Standard Anomaly Index (SAI) values of the three areas in Eastern Ethiopia for the Baseline Years 1980-2017

Location	PCI (%)				SAI			
	Annual	<i>Bega</i>	<i>Belg</i>	<i>Kiremt</i>	Positive Anomalies		Negative Anomalies	
					No. of years	% proportion	No. of years	% proportion
Haramaya	15.81	19.28	16.15	10.22	17	44.74	21	55.26
Chiro	16.17	18.84	9.23	10.62	23	60.53	15	39.47
Kombolcha	18.77	20.09	15.80	12.08	12	31.58	26	68.42

A higher precipitation concentration index value indicates that precipitation is more concentrated to a few rainy months during the year and vice versa (Zhao *et al.*, 2011). Irregular rainfall patterns result in high risk of drought and intra-seasonal dry spell, leading to low crop yields and sometimes total crop failures (Kinoti *et al.*, 2010). Therefore, potato production could be adversely affected particularly if the scarcity of water coincides with the critical growth stage of the crop, especially during tuber initiation and tuber bulking period. This suggestion

is consistent with the fact that the potato plant is most sensitive to water stress during tuber initiation and bulking (Blom-Zandstra *et al.*, 2015). However, the distribution of rainfall matters during growth of the crop. Except PCI values of Kombolcha for *Belg* season which were significant, the Man-Kendall trend test of both seasonal and annual precipitation concentration indices of all study districts showed non-significant trends (Table 5).

Table 5. Man-Kendall trend test of Precipitation Concentration Index (PCI) for three locations in eastern Ethiopia for the baseline years of 1980-2017

Location	Rainfall(mm)	Annual	<i>Bega</i>	<i>Belg</i>	<i>Kiremt</i>
Haramaya	Sen's slope	0.05	-0.05	-0.07	0.02
	MK	1.26	-0.59	-0.68	1.51
Chiro	Sen's slope	0.001	0.02	-0.06	0.01
	MK	0.03	0.19	-0.53	0.67
Kombolcha	Sen's slope	-0.05	0.112	0.11	-0.05
	MK	-0.60	1.23	2.16**	-1.36

Standard Anomaly Index (SAI)

From the 38-year average total rainfall data of each site, the greater portion of the years showed negative Standard Anomaly Index (SAI) values for Haramaya and Kombolcha (Table 4). This indicates that the mean annual precipitation amounts were below the mean annual precipitation values of long term rainfall data for the districts. The result also indicates that many of the years varied in mean annual precipitation compared to the long term mean values. This signifies the availability of year to year variability in rainfall which may put crop production at the risk of moisture stress. However, *Chiro* had the highest (60.53%) proportion of positive SAI values. The study also revealed that the intensity and magnitude of drought occurrence varied across the districts. This might show non-uniform distribution or random variability in rainfall.

In the duration from 1980 to 2017, drought occurred seven times in *Haramaya* and *Chiro* districts,

resulting in significant reductions in agricultural production. Moreover, the frequency of drought had been very high from 2008 to 2013 for *Chiro*. Comparatively, *Kombolcha* showed the lowest frequency of drought followed by *Haramaya* and *Chiro*. This could be attributed to the higher elevation of Kombolcha district than the other two districts, which may attract clouds for enhanced precipitation. In agreement with this suggestion, Seleshi and Zanke (2004) also revealed that altitude greatly influences climate of Ethiopia and creates microclimate ranging from cool highlands to hot desert climate.

At the Haramaya station, a moderate drought occurred in 1995 and severe droughts occurred in 1980, 1985, 1992, 2002 and 2012. However, other study years showed no drought occurrence. On the other hand, Kombolcha district showed moderate drought occurrence in 1984 and 2002. Nevertheless, *Chiro* district had moderate drought conditions in 1980, 2008, 2012, and 1984; severe drought in 1995 and 2011 and extreme drought in 1996 and 2013. This result implies

that recently dry years have occurred repeatedly in Haramaya district; hence, the rainfall trend signifies the need for suitable adaptation options and identifying causes of frequent drought occurrences in the areas to cope with climate change. In comparison to Chiro, Kombolcha station showed a high negative anomaly. Events of drought occurring

early in the growing season reduce the number of tubers per plant while a single and intermittent drought events during tuber bulking can interrupt and inhibit future tuber bulking which not only decrease potato grade in terms of tuber size and quality but also lower the overall yields (Blom-Zandstra *et al.*, 2015).

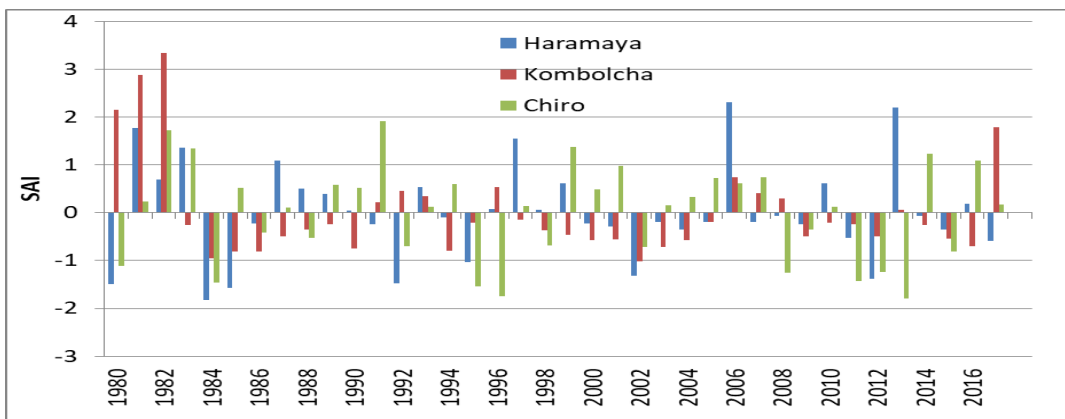


Figure 1. Standardized Anomaly Index (SAI) of three stations in Eastern Ethiopia over the period 1980-2017

The results of this study concur with the findings that severe and extreme drought occurred two times both in Haramaya and Chiro districts; thus, from the 1950s to 1980s, droughts occurred on average once per decade, and recently, it has occurred once every three years in Ethiopia (Block, 2008). Concurrent with these findings, the World Bank (2006) reported that 16 drought events were experienced from 1980 to 2004 which makes Ethiopia the most drought-affected country. According to Haile (1986), drought occurs every three to four years in the northern and every six to eight years in other parts of Ethiopia. Conversely, in the current study, the

SAI result revealed that drought occurrence is not consistent with forecasts in all the study areas. The current results show a ten-year interval for severe drought occurrence at Haramaya district.

Trend analysis of observed temperature and rainfall

Trend test for Annual and seasonal rainfall variability analysis

For the study period (1980–2017), the annual rainfall in Haramaya, Chiro and Kombolcha districts decreased by 44.84 mm, 73.91 mm, and 29.03 mm,

respectively (Table 6). Non-significant decreasing trends were observed in the annual rainfall in all study districts. In contrast to this study, Amogne *et al.* (2018) indicated a significantly decreasing trend both for the main rainy season (*Kiremt*) and for yearly annual rainfall. As per the Mann-Kendall trend test, the amount of *Belg* rainfall of Haramaya decreased by 10.38 mm per decade, though not statistically significant. *Kiremt* season rainfall showed a significant

increasing trend (84.78 mm) whereas the *Belg* season rainfall showed a decreasing trend (39.44 mm) for Haramaya district, which could be a sign for rainfall distribution change/variability rather than the total amount. Thus, potato productivity in the study area may be impacted either directly or indirectly as a result of both seasonal and annual rainfall variability.

Table 6. Annual and seasonal Man-Kendall trend test for rainfall parameters for three locations in eastern Ethiopia for the period of 1980–2017.

Location	Variable	Season	ZMK	Sen's slope (Slope)
Haramaya	RF (mm)	Annual	-0.60	-1.180
		Bega	0.04	0.041
		Belg	-0.78	-1.038
		Kiremt	2.21**	2.231
Chiro	RF (mm)	Annual	-0.45	-1.945
		Bega	0.1	0.1
		Belg	-0.7	-1.75
		Kiremt	-0.1	-0.259
Kombolcha	RF (mm)	Annual	-0.14	-0.764
		Bega	0.69	0.69
		Belg	-0.30	-4.636
		Kiremt	0.85	1.547

Where, ZMK is Mann–Kendall trend test, Slope (Sen's slope) is the change (days)/annual; ** is statistically significant at 0.05 probability level.

A non-significant decreasing trend in *Belg* season rainfall was Similarly, Amogne *et al.* (2018) reported a non-significant decreasing trend in *Belg* season rainfall. Negash *et al.* (2013) investigated the spatio-temporal variability of annual and seasonal rainfall in Ethiopia and reported a decreasing trend in *Kiremt* and annual rainfall in northern, northwestern and

western parts of the country while observing an increasing trend in annual rainfall in a few grid points in eastern parts of the country. However, the results of this study showed a decreasing trend in annual rainfall. The findings of this study provide the basis for farmers to adjust their land preparation and planting dates to coincide with periods/months of

reliable and uniformly distributed rainfall. Furthermore, the occurrence of late blight disease of potato is highly interrelated with both the amount and distribution of rainfall during the crop growing period. Hence, *Kiremt* season rainfall increment could make a suitable condition for late blight disease whilst the reduction in *Belg* season rainfall could have effect on the yield of potato.

Man-Kendall test for temperature variability

The mean annual maximum temperature increased by 0.29°C , and 0.11°C per decade, and minimum temperature increased by 0.18°C and 1.19°C per decade for Haramaya and Chiro districts, respectively (Table 7). Both annual and seasonal maximum temperature in Haramaya station showed an increasing trend which was significant at the level of 95% whereas minimum temperature revealed a positive trend even if non-significant in annual and *Kiremt* season. The variability (CV value) of minimum temperature was higher than that of maximum temperature for Chiro (Table 7). Mann-Kendall trend test output for Chiro indicated an increasing trend for both maximum and minimum temperatures. However, the change was statistically significant for *Bega* and *Kiremt* seasons minimum temperature. This non-significant trend during *Kiremt* season could be

ascribed to rainfall that can diminish the effect of maximum temperature change, which occurs if rainfall variability is not found at a significant level unless other factors aggravate and facilitate the impact.

Man-Kendall test for minimum temperature for Haramaya resulted in a non-significant increment, both for annual and *Belg* season. However, *Bega* and *Kiremt* season showed significantly increasing trends at 90%. In the case of Chiro district, the minimum temperature for *Bega* and *Kiremt* seasons showed significant increasing trends at 95% and 90%, respectively (Table 7). On the other hand, the rate of change of mean temperature for Haramaya and Chiro districts were 0.023°C and 0.051°C , respectively. The overall increase in annual temperature observed in the study areas is, therefore, largely attributed to the increase in the minimum temperature. This could have its own impact on the *Belg* season potato production. These results signify that analyzing and finding suitable adaptation mechanisms for potato crop is important. In line with this result, Amogne *et al.* (2018) also indicated a significantly increasing trend in the mean and minimum temperatures through time while the trend for maximum temperature exhibited a non-significantly increasing trend.

Table 7. Annual and seasonal Man-Kendall trend test for temperature parameters for two locations in eastern Ethiopia for the Period of 1980-2017

Location	Variables	Season	ZMK	Sen's slope (Slope)
Haramaya	Tmax (°C)	Annual	2.81**	0.029
		Bega	2.29**	0.022
		Belg	3.42**	0.038
		Kiremt	3.39**	0.028
	Tmin (°C)	Annual	0.77	0.018
		Bega	1.84*	0.030
		Belg	0.18	0.003
		Kiremt	1.82*	0.034
Chiro	Tmax (°C)	Annual	0.27	0.011
		Bega	-0.67	-0.010
		Belg	1.06	0.024
		Kiremt	0.78	0.009
	Tmin (°C)	Annual	1.45	0.119
		Bega	2.31**	0.092
		Belg	1.27	0.140
		Kiremt	1.66*	0.114

Where, ZMK is Mann–Kendall trend test, Slope (Sen's slope) is the change (days)/annual; **, * is statistically significant at 0.05 and 0.1 probability level.

The observed increasing trend of both maximum and minimum temperature could have effect on potato tuber initiation and bulking. Consistent with this suggestion, temperature patterns influenced potato in tuberization stage which in turn reduced the yield and quality of the crop (Borah *et al.*, 1962). Wolf *et al.* (1990) reported that high temperatures during the long day favors assimilate partitioning to the above ground vegetative parts and results in increments in aboveground biomass and plant height while resulting in reduced partitioning of assimilates for tuber bulking at night, which requires lower soil temperatures. During the study period (1980–2017), in the months of June and July, rainfall decreased by 4.64 mm and 46.85 mm and also increased by 66.46 mm and 80.33 mm for

Haramaya and Kombolcha districts, respectively. Similarly, the rainfall for the month of August increased by 14.71 mm and 73.53 mm for Haramaya and Kombolcha stations, respectively, whereas decreased by 25.95 mm for Chiro district. This is also an indication that the monthly distribution of rainfall was impacted during the last three decades. For potato, the critical growing months are July and August for Haramaya during which flower initiation and high vegetative growth proliferate. Concurrently, the increase in rainfall during this period creates a suitable condition for the most important fungal and bacterial disease of the crop. Therefore, potato production during the rainy season should be accompanied by the use of fungicides and bactericides or improved varieties

that are resistant or tolerant to the disease.

Conclusion

The results of this study have revealed considerable variability and trends of temperature and rainfall over the 38-year period at three districts in eastern Ethiopia. Analysis of the data indicated that temperatures have increased over time and precipitation has exhibited high variability across seasons and the districts. The results have also indicated that overall rainfall amounts have reduced. This variation has led to more frequent occurrences of drought. The study further revealed that the *Belg* season was more variable than the main rainy (*Kiremt*) season in terms of rainfall amount and distribution. With the exception of PCI values of Kombolcha for *Belg* season which was significant, the Man-Kendall trend test of both seasonal and annual precipitation concentration index of all study districts showed non-significant trend. This problem would lead to increased vulnerability of farmers to shocks and induce them to replace potato with other crops that are less sensitive to climate variability such as drought, diseases, etc. The observed variability in temperature in particular signifies negative impact on the growth and development cycle of potato. This implies loss of cash income for farmers as well as exacerbated household food and nutrition insecurity. This means production of potato in the study area should suit the changing climate and

management of the crop should be designed to suit weather variables. Therefore, it is important to create regional and national awareness on the existing as well as impending climate variability in potato producing areas, identify adaptation options for improving of the crop and increase farmers' resilience to climate change. Future research should be geared towards developing drought tolerant as well as disease-resistant potato varieties for cultivation during both off-season using small-scale irrigation and during the main rainy season in a double cropping system to enhance farmers' income, food security, and resilience to climate shocks.

Acknowledgments

Thanks are due to the Ethiopian Ministry of Science and Higher Education (MoSHE) for funding the research as part of the PhD study of the first author. The authors also thank Haramaya University for facilitating the study and the field work; and the Ethiopian National Meteorological Service Agency for kindly providing the rainfall data free of charge.

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Yield Stability Analysis of Soybean Varieties (early set) in Western Oromia, Ethiopia

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Abstract

Over the decades, very limited early maturing soybean varieties were developed and released in Ethiopia. This experiment was conducted to identify adaptable, high yielding and stable variety (s) among the released but potential early maturing soybean varieties for Western Oromia. The influences of genotype by environment interaction on grain yield of soybean varieties were also examined. Seven early maturing soybean varieties were evaluated at Bako for two years (2016 and 2017), at Billo and Gute during 2016, and at Chewaka and Uke during 2017 main cropping seasons. Combined analysis of variance showed that grain yield was significantly ($P < 0.01$) affected by environments, genotypes and their interactions; accounting for 51.1, 35.9 and 12.2% variations, respectively. The first two principal components ($IPCA_1$ and $IPCA_2$) were used to create a two-dimensional Genotype and Genotype by Environment (GGE) biplot and explained 84.49 and 9.1% of the total sums of squares of $G \times E$ interaction, respectively. Soybean variety Nyala was identified as the most stable and high yielding genotype in the test environments. In addition, Boshe and Coker-204 also showed better stability & high yield performance, whereas variety Nova was identified as the least stable and low yielding. Therefore, among early set soybean varieties, Nyala, Boshe and Coker-204 were recommended for further demonstration and large scale production in the test environments and similar agro-ecologies of western Oromia.

Keywords: AMMI, Genotype, *Glycine max*, Maturity

Introduction

Soybean [*Glycine max* (L.) Merrill] is one of the most important oil grain legume crops in the world (Laswai *et al.*, 2005). Soybean is rich in nutritional value due to its high protein and oil content as well as aspects of its functional composition, such as is flavones (Liu *et al.*, 2017). In Ethiopia, soybean is used for a variety of purposes including preparation of different kinds of soybean foods,

animal feed and soy milk (Hailu and Kelemu, 2014). Soybean is classified in different maturity groups such as early, medium and late maturing varieties based on to the length of growing period from planting to maturity. This phenological attribute is determined by two abiotic factors: photoperiod and temperature (Mourtzinis and Conley, 2017), and these factors can dictate the most suitable maturity groups of soybean varieties for a particular geographical

location (Liu *et al.*, 2017). Therefore, identification of different maturity soybean varieties that fit specific agro-ecologies of western Oromia is an alternative

To maintain improved agricultural productivity, the development of varieties with high yielding potential is the ultimate goal of plant breeders in a crop improvement program. In the recent years of soybean breeding in Ethiopia, special focuses have been given to develop varieties with improved grain yield, good seed color and size, and resistant to major diseases. In addition to high yielding potential, a successfully developed new cultivar should have a stable performance and broad adaptation over a wide range of environments. However, variation from season to season and from place to place within a shorter distance is among the most important features of the Ethiopian environmental conditions (Tolessa and Gela, 2014). In such cases, genotype by environment (G x E) interaction effect is expected to be greater.

Genotypes exhibit fluctuating yields when grown in different agro-climatic zones. This complicates demonstration of the superiority of particular genotypes. Multi-environment yield trials are crucial to identify adaptable high yielding cultivars and discover sites that best represent the target environment (Tolessa and Gela, 2014; Dabessa *et al.*, 2016). Failure of genotypes to respond consistently to variable environmental conditions is attributed to genotype by environment

interaction (EI). Knowledge of genotype and genotype by environment interaction (GGE) is advantageous to have cultivar that gives consistently high yield in wider range of environments and to increase efficiency of breeding program and selection of best genotypes.

Genotype and genotype by environment interaction (GGE) biplot allows for assessing the performance of genotypes in the tested environments. Phenotypic variation of genotypes across environments results from environmental and genotypic variations and genotype by environment interaction. Environmental variation is the dominant source of phenotypic variation (Amare and Tamado, 2014; Funga *et al.*, 2017). Therefore, multi-environment trials (MET) are required to identify specific and the general adaptability of genotypes. In western Oromia, where this study was conducted, the yields of early maturing soybean varieties were very low due to different biotic and abiotic factors. Therefore, this study was aimed at identifying high yielding and stable early maturing soybean varieties across environments and examining the influence of GEI on grain yield of soybean varieties.

Materials and Methods

Seven early set soybean varieties (Table 1) were evaluated at six locations for two consecutive years during 2016 and 2017 main cropping

seasons. The study sites included Billo and Gute during 2016, Chewaka and Uke during 2017 and at Bako during 2016 and 2017 main cropping season (Table 2). Each plot consisted of four rows of 4-meter length, with 40 cm

and 10 cm spacing between rows and plants, respectively. Fertiliser rate of 100 kg ha⁻¹ NPS was applied at planting. All other management practices were applied as routinely used in the study areas.

Table 1 Pedigree, origin, area of adaptation and year of release of soybean varieties used for the study

Variety	Pedigree	Source center	Adaptation Altitude (m.a.s.l)	Year of Release	Maturity (days)
Boshe	(IAC-13-1)	BARC/OARI	1200-1900	2008	100-110
Coker-204	NI	HwARC/SARI	700-1700	1981	100-110
Crawford	NI	HwARC/SARI	1300-1850	1974	90-100
Jalale	AGS-217	BARC/OARI	1300-1850	2003	100-110
Nova	NI	HwARC/SARI	1200-1700	2012	90-100
Nyala	NI	HwARC/SARI	800-1700	1974	100-110
Williams	NI	HwARC/SARI	1000-1700	1974	90-100

NI = not identified

Table 2: The study Environments and their main agro ecological features

Location	Year	Longitude	Latitude	Altitude (m.a.s.l)	RF (mm)	Soil type
Bako	2016 & 2017	37°09'E	09°06'N	1650	1431	Sandy-clay
Gute	2016	E:036°38.196'	N:09°01.061'	1915	NI	Clay
Billo	2016	E:037°00.165'	N:09°54.097'	1645	1500	Reddish brown
Chewaka	2017	036.11703E	09.98285N	1259	NI	Clay loam
Uke	2017	E:036°32..391'	N:09°25.082'	1319	NI	Sandy loam

NI = not identified RF= Rainfall

Additive Main Effects and Multiplicative Interaction (AMMI) model was used to assess genotype by environment interaction (GEI) pattern. AMMI model is expressed as:

$$Y_{ger} = \mu + ag + \beta e + \sum n \lambda n \gamma g n d e n + eger + pge \dots \dots \dots \text{Equation 1}$$

Where: Y_{ger} is the observed yield of genotype (g) in environment (e) for replication (r);

Additive parameters: μ is the grand mean; ag is the deviation of genotype g from mean, βe is the deviation environment e;

Multiplicative parameters: λn is the singular value for IPCA, $\gamma g n$ is the genotype eigenvector for axis n, and $d e n$ is environment eigenvector; $eger$ is error term and pge is PCA residual.

Accordingly, genotypes with low magnitude regardless of the sign of interaction principal component analysis scores have general or wider adaptability while genotypes with high magnitude of IPCA scores have specific adaptability (Gauch, 1992; Umma *et al.*, 2014).

AMMI stability value of the i^{th} genotype (ASV) was calculated for each genotype and each environment according to the relative contribution of IPCA_1 to IPCA_2 to the interaction SS as follows (Purchase *et al.*, 2000):

$$\text{ASV}_i = \sqrt{\left[\frac{\text{SS}_{\text{IPCA1}}}{\text{SS}_{\text{IPCA2}}} [\text{IPCA1}_{\text{score}}] \right]^2 + [\text{IPCA2}_{\text{score}}]^2} \dots\dots\dots \text{Equation 2}$$

Where: $\text{SS}_{\text{IPCA1}}/\text{SS}_{\text{IPCA2}}$ is the weight given to the IPCA_1 value by dividing the IPCA_1 sum of squares by the IPCA_2 sum of squares.

Based on the rank of mean grain yield of genotypes (RY) across environments and rank of AMMI stability value (RASV), the Genotype Selection Index (GSI) was calculated for each genotype, which incorporate both mean grain yield (RY) and stability I (GSI) (Purchase *et al*2000).

$$\text{GSI} = \text{RASV} + \text{RY} \dots\dots\dots \text{Equation 3}$$

Genotype plus genotype by environment variation (GGE) was used to assess the performance of genotypes in different environments. The environmental effects were removed from the data and results obtained from the data were used to calculate environment and variety scores and these scores were used to plot the standard principal component bi-plots (Yan and Kang, 2003). Analysis of Variance (ANOVA) and Additive Main Effect and Multiplicative Interaction (AMMI) analysis and GGE bi- plots were performed using Gen Stat 18th edition statistical package (GenStat, 2016).

Results and Discussion

Combined analysis of variance

There were statistically significant differences ($P < 0.01$) among soybean varieties, environments and their interaction for grain yield (Table 3). This indicates the presence of genetic

variation among the soybean varieties and possibility to select high yielding and stable variety (s); the environments were variable and the responses of soybean varieties across environments are also variable.

Table 3. Combined Analysis of variance for grain yield of early soybean varieties evaluated at across environments

Source of variation	Degree freedom	Mean square
Environments	5	5591561**
Genotypes	6	3280014**
Block within environment	2	90706 ^{ns}
Interaction	30	223462**
Error	82	21356
CV (%)	8.5	

**= significant at $P = 0.01$, ns = none significant

Performance of genotypes across environments

Table 4 shows the average mean grain yield of seven soybean varieties evaluated across the test environments. The pooled mean grain yield ranged from 894.5 to 2189.6 kg ha⁻¹. Among all the varieties, the highest grain yield was obtained from Coker-204 variety (2189.6 kg ha⁻¹) followed by Nyala (2008.6 kg ha⁻¹) and Jalale (1708 kg ha⁻¹). However, Nova was the lowest

yielder (894.5 kg ha⁻¹). This difference could be due to their genetic potential. Coker-204 was the top ranking genotype at Bako in both years, at Gute and Chewaka. Whereas, Nyala and Boshe ranked first at Billo and Uke, respectively. The difference in yield rank of early set soybean varieties across the test environments revealed high genotype by environment interaction.

Table 4. Mean grain yield (kg ha⁻¹) of seven soybean varieties evaluated at six environments

Varieties	Locations						
	Bako-2016	Bako-2017	Gute	Billo	Chewaka	Uke	Mean
Williams	1870	1471.6	2353.7	1318.3	565.7	1377.1	1542.8
Crawford	2227	1629.9	2389.53	1839.8	957.9	975.7	1669.5
Nyala	2425.4	2390.8	2363.6	2463.2	1089.4	1319.2	2008.6
Nova	1458.4	897.9	7716	915.7	598.6	724.8	894.5
Boshe	2485.5	2546.7	2230.8	2254.8	1096.7	1339.1	1992.3
Coker-204	2655.9	2723.6	2511	2453.2	1472.9	1321.3	2189.6
Jalale (check)	2214.1	2335.9	2080.1	1474.9	969.4	1174	1708.1
LSD (0.05)	206.9	199	188.3	489.5	116.4	191.9	116.4
CV (%)	5.3	5.6	5.04	14.8	6.8	9.2	10.2

AMMI model analysis

AMMI model analysis of variance for grain yield is presented in Table 5. This analysis also revealed presence of highly significant ($P < 0.01$) differences among soybean varieties for grain yield performance. From the total treatment sum of squares, the largest portion was due to environments main effect (51.1%) followed by varietal main effect (35.9%) and the effect of genotype by environment interaction was 12.2%. A large yield variation explained by environments indicated that the existence of both spatial and temporal diversity in test-environments, with large differences among

environmental means causing most of the variation in grain yield. In line with this result, Tolessa and Gela (2014) reported large yield variation of common bean genotypes due to environments. This also indicates the existence of a considerable amount of deferential response among the evaluated soybean varieties to changes in growing environments and the differential discriminating ability of the test environments. The higher percentage of G x E interaction was explained by IPCA-1 (4.8%); followed by IPCA-2 (4.4%) and, therefore, used to plot a two dimensional GGE biplot. Amare and Tamado (2014), and Temesgen *et al.* (2014) suggested the

most accurate model for AMMI could be predicted by using the first two IPCA.

Table 5: ANOVA for grain yield using AMMI mode

Source of variation	DF	Sum of square	Explained SS (%)	Mean square
Total	125	56274352		450195
Treatments	41	54341756		1325409**
Genotypes	6	19680083	35.9	3280014**
Environments	5	27957806	51.1	5591561**
Block	12	386230	0.7	32186 ^{ns}
Interactions	30	6703867	12.2	223462**
IPCA 1	10	2717387	4.8	271739**
IPCA 2	8	2480532	4.4	310067**
Residuals	12	1505948		125496
Error	72	1546366		21477

Key: ns= non- significant, **= significant at 1% and *= significant at 5% probability level. SS= sum of square, DF= degree of freedom.

AMMI biplot analysis

AMMI biplot graph with X-axis plotting $IPCA_1$ and Y-axis plotting $IPCA_2$ scores illustrate stability and adaptability of soybean varieties to tested environments (Fig. 1). The more the IPCA scores approaches to zero, the more stable or adapted the genotypes is over all the test environments. The variation of seed yield for each variety was significant at different environments. Jalale and Nyala varieties were specifically adapted to high yielding environments (Fig. 1). Considering the $IPCA_1$ score, Nova, Crawford and Williams were the most unstable varieties and also adapted to low yielding environments. Boshe and Coker-204 were more

stable in comparison to other varieties. Boshe and Coker-204 varieties were near to zero IPCA by which it were shown to have higher stability for seed yield than other soybean varieties (Fig. 1). Coker-204 had highest seed yield followed by Boshe variety. Boshe, Coker-204 and Jalale varieties had higher GEI at environments of Bako. It has been reported that the varieties that have the lowest IPCA score in AMMI biplot are an indication of the stability or adaptation over environments (Dolinassou *et al.*, 2016). It is further stated that the greater the IPCA scores, negative or positive, the more specific adapted is a genotypes to certain environments.

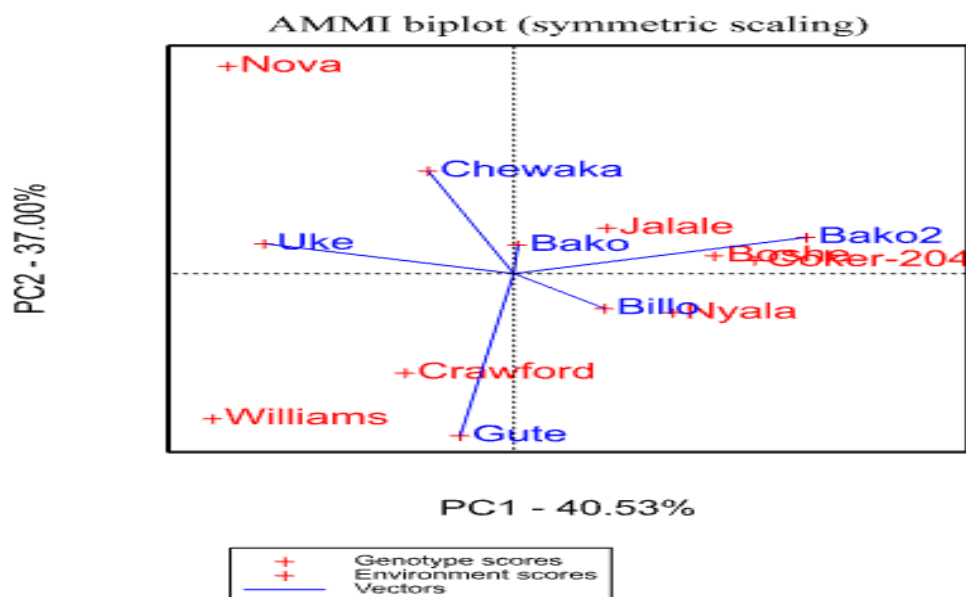


Fig 1. Biplot of interaction principal component axis (IPCA₁) against interaction principal component axis (IPCA₂) of early set soybean varieties evaluated across six environments in Western Oromia.

AMMI stability value and genotype selection index

The IPCA₁ and IPCA₂ scores for each variety and also the AMMI Stability Value (ASV) with its ranking for seven early set soybean varieties are presented in Table 6. A genotype/variety with least ASV score is the most stable (Purchase *et al.*, 2000). Accordingly, Boshe, Jalale and Crawford were the most stable. On the other hand, Williams, Nyala and Nova varieties were the most unstable. This

measure is essential in order to quantify and rank of varieties according to their seed yield stability. Genotype with the smallest Genotype Selection Index (GSI) value is considered as the most stable with high seed yield (Farshadfar, 2008; Dabessa *et al.*, 2016). Based on the GSI result, the most desirable variety for selection of both stability and high seed yield were Boshe and Coker-204 (Table 6), which was in line with the result of AMMI and GGE biplot.

Table 6. AMMI stability value, genotype selection index and ranks based on grain yield of seven soybean varieties evaluated at six locations in Western Oromia

Varieties	Yield	ASV	RY	RASV	GSI
Boshe	1992.27	13.92	3	2	5
Coker-20	2189.64	28.09	1	4	5
Crawford	1669.47	12.19	5	1	6
Jalale	1708.06	25.02	4	3	7
Nova	894.5	34.04	7	5	12
Nyala	2008.6	43.69	2	6	8
Williams	1542.82	45.69	6	7	13

Where, ASV = AMMI stability value, RY = Rank of yield, RASV = Rank of AMMI stability value and GSI = Genotype selection index

GGE biplot analysis

In GGE biplot (Fig. 2), $IPCA_1$ and $IPCA_2$ explained 84.49 and 9.1%, respectively, of soybean varieties by environment interaction and made a total of 94.1%. Other studies conducted on groundnut by Amare and Tamado (2014) and white lupines by Atnaf *et al.* (2017) explained an interaction of 81.8 and 63.4%, respectively, extracted from $IPCA_1$ and $IPCA_2$. An ideal genotype is defined as genotype which having the greatest $IPCA_1$ score (mean performance) and with zero GEI, as represented by an arrow pointing to it (Fig. 2). A genotype is more desirable

if it is located closer to the ideal genotype. Thus, using the ideal genotype as the center, concentric circles were drawn to help visualize the distance between each genotype and the ideal genotype. Therefore, the ranking based on the genotype-focused scaling assumes that stability and mean yield are equally important. In this study, Nyala, Coker-204 and Boshe varieties which fell closest to the ideal genotype were identified as the most desirable genotypes as compared to the rest of the tested soybean varieties (Fig 2). Supportive results were reported by Dabessa *et al.* (2016) for groundnut.

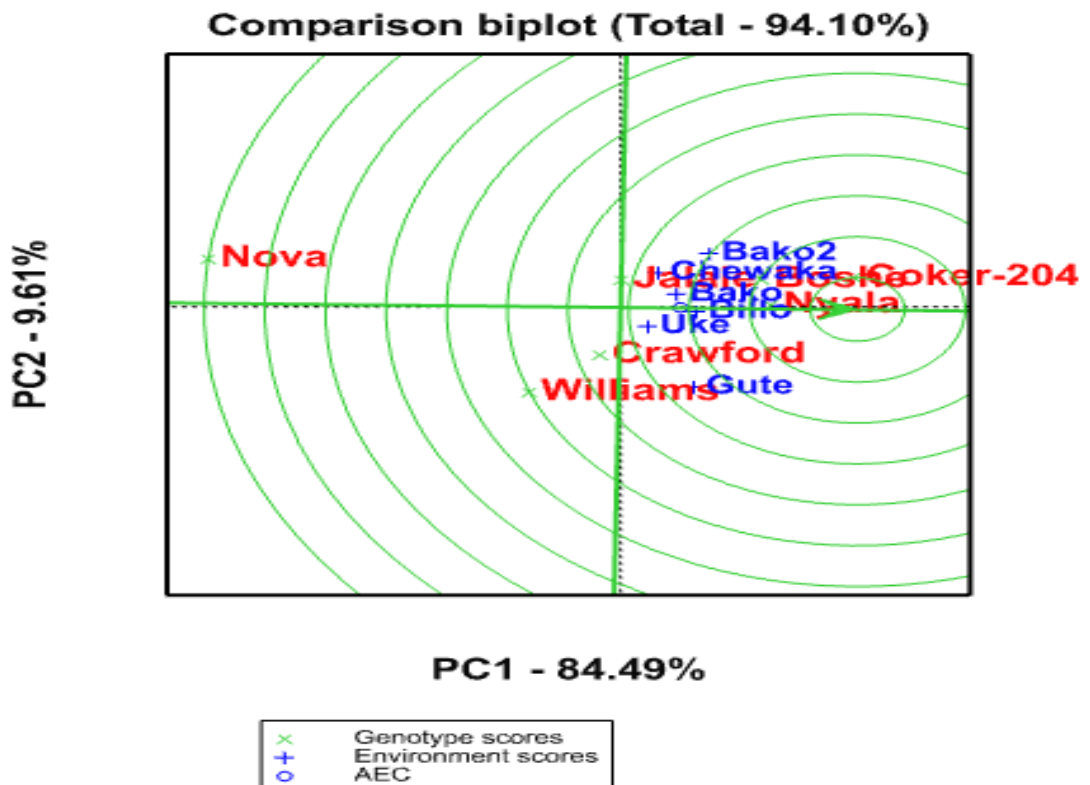


Fig 2: GGE-biplot based on genotype-focused scaling

Discriminating ability and representativeness of the environments

An environment is more desirable and discriminating when located closer to the centre circle or to an ideal environment (Naroui *et al.*, 2013). A test environment with a small angle with the AEA is more representative than other environments (Yan and Rajcan, 2003). Therefore, in the present study, Bako and Billo locations were identified as relatively the most discriminating environment as compared to Chewaka, Gute and Uke (Fig. 3). Thus, Bako and Billo were identified as the most conducive

environments for soybean production. Both discriminating ability and representativeness view of the GGE biplot are the most important measures of testing environment, which provide not only valuable but also unbiased information about the tested genotypes (Yan and Kang, 2003). Yan and Tinker (2006) also reported that the length of environmental vector is directly proportional to the standard deviation within the respective environments and help to know the discriminating ability of this target environment i.e. an environment with long environmental vector has high discriminating ability and vice versa.

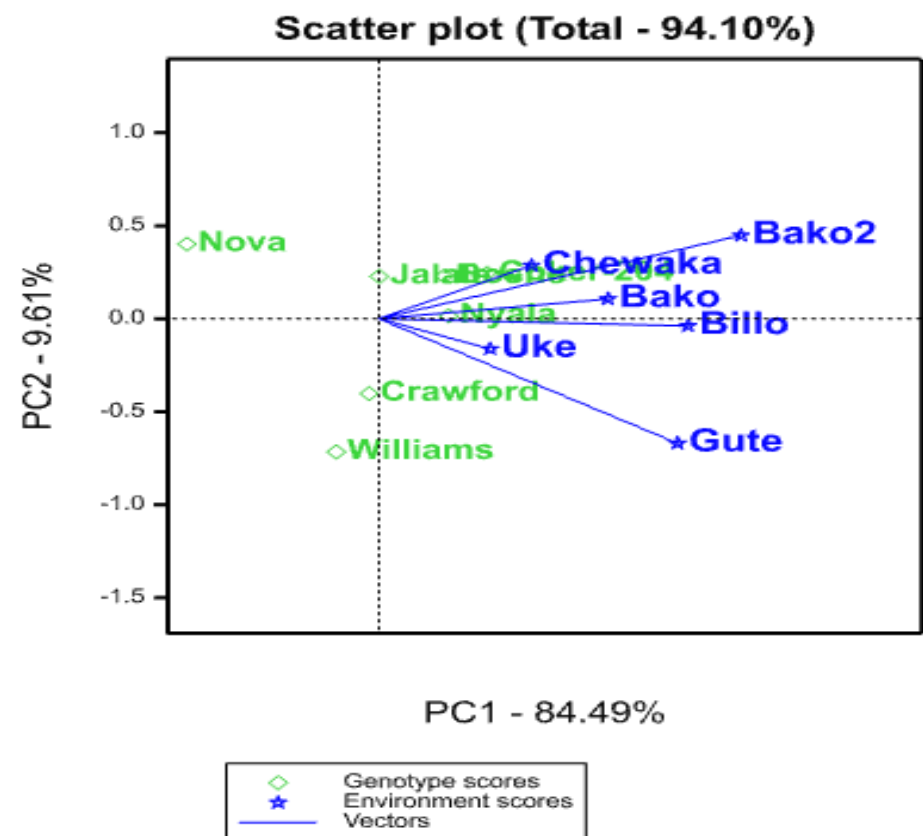


Fig 3. The vector view of GGE biplot which shows the interrelation ships among the test environments in Ethiopia

Conclusion

Combined analysis of variance indicated that grain yield performances of the tested varieties were highly influenced by environment, varieties and GEI. This indicated that a particular variety does not exhibit uniform performance under different environmental conditions or different varieties may respond differently to a specific environment. The varieties and environment main effects and genotype-by-environment interaction effect were highly significant for early set soybean varieties. The environment contributed most to the variability in grain yield. Varieties Nyala, Boshe and Coker-204 were close to the ideal genotype and can thus be used as bench marks for the evaluation of early set soybean genotypes in western Oromia. Considering simultaneously mean yield and stability, Boshe and Coker-204 were the best early maturing soybean varieties that fit in the study areas.

Acknowledgements

This study was funded by Oromia Agricultural Research Institute, Bako Agricultural Research Center. The pulse and oil crops research team members of Bako Agricultural Research Center assisted in recording field data.

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Genotype by Environment Interaction and Grain Yield Stability of Striga Resistant Sorghum [*Sorghum bicolor* (L.) Moench] Genotypes in Ethiopia

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Abstract

Forty-nine sorghum varieties (hybrids and open pollinated) were evaluated across five environments during the 2016 main cropping season. The objectives of this study were to estimate the magnitude and nature of genotype by environment interaction for grain yield and to determine yield stability of striga resistant sorghum genotypes in the dry lowland areas of Ethiopia. The study was conducted using a simple lattice design with two replications. The result of the combined analysis of variance for grain yield revealed highly significant ($P \leq 0.001$) difference among environment (E), genotype (G) and genotype $\times$ environment interaction (G $\times$ E). Environment explained 76.13% of the total variation, whereas G and G $\times$ E explained 11.21% and 12.66% of the total variation, respectively. The magnitude of the environment was 6.8 times greater than the genotype, implying that most of the variation in grain yield was due to the environment. Based on combined analysis of variance over locations, the mean grain yield of environments ranged from 588 kg ha⁻¹ at Humera to 4508 kg ha⁻¹ at Sheraro. The highest yield was obtained from ESH-1 (3278 kg ha⁻¹), while the lowest was from K5136 (735 kg ha⁻¹) and the average grain yield of genotypes were 2184 kg ha⁻¹. AMMI and GGE biplot stability models were used to identify stable genotypes for partitioning the G $\times$ E into the causes of variation and the best multivariate models in this study. Thus, AMMI model was used to identify superior genotypes for specific and wide adaptation. Accordingly, K7439, K7252 and K7437 were specifically adapted to low environments of Humera, Kobo and Fedis, whereas, ESH-1 and K7233 were the better hybrids for favorable environments of Mehoni and Sheraro, respectively. Moreover, the GGE biplot identified two different sorghum growing mega-environments for grain yield. The first mega environment includes higher (Mehoni) to low yielding (Humera, Kobo and Fedis) environments, respectively, with the winner genotype ESH-1 and the second mega environment containing the highest yielding environment in Sheraro area with winner genotype K7233. Thus, the which-won-where biplot showed two winning genotypes in two mega environments. However, the standard hybrid check, ESH-1 won in most of the environments. Therefore, ESH-1 can be recommended for wider cultivation due to better grain yield and stability performance across the test environments in the dry lowland areas of Ethiopia.

Keywords: AMMI, GEI, Genotype, GGE biplot, Mega environment

Introduction

Sorghum [*Sorghum bicolor* (L.) Moench] belongs to the grass family Poaceae, is the fifth most important cereal crop globally and occupies the second position among the staple food grains in semi-arid tropics. Sorghum is called as camel of crops due to high tolerance of prolonged drought. The crop also withstands temperature stress and high photosynthesis efficiency; it is considered as an important plant in arid and semi-arid regions (Anagholi, 2000). The annual wild and domesticated sorghums are diploid ($2n = 2x = 20$) and are of tropical origin C4 crop. Ethiopia is one of the center of origin and diversity for sorghum (House, 1985; FAO, 1995; Tesfaye *et al.*, 2011), which indicates the availability of enormous genetic variability in both cultivated and wild sorghums (Taye *et al.*, 2016; Tesfaye *et al.*, 2016).

Thus, the Ethiopian sorghum collections have been used as a main sources of several genes for important traits globally (Tefaye *et al.*, 2017), including stay green genes for post flowering drought tolerance (Kebede *et al.*, 2001; Haussmann *et al.*, 2002), disease resistance, better grain quality and increased yield potential (Prasada and Mengesha, 1981) and have been used widely in many national and international sorghum breeding programs. In Ethiopia, sorghum is produced by five million small holder farmers and its production is estimated to be four million metric tons from

nearly two million hectares of land, giving the potential average grain yield of around two tons per hectare. It is ranked third in area coverage and fourth in total production (CSA, 2016).

However, low yields of sorghum have been recorded due to a number of biotic and abiotic constraints. Among the biotic constraints, *striga* is becoming the major epidemic in most of sorghum growing areas, where soil fertility (nutrient deficiency) and moisture stress are limiting factors, *i.e.* *striga* is rapidly expanding in areas where the soil has low fertility and drought is frequent. Nationally, *striga* causes annual yield loss as high as 65-70% and, at times, leaves plots uncultivated (Gebisa, 2007). In order to address the constraints affecting sorghum, and increase its production, the National Agricultural Research Systems (NARS) in collaboration with international research centers like, ICRISAT and Purdue University are developing hybrid sorghums.

Hybrid sorghums are known to be high yielder than the open pollinated and landrace cultivars to about 20 to 60% (Atokple, 2003). Beside, hybrids have been found better suited to moisture stress environments due to their earliness, better adaptation and stability (Fantaye and Hintsu, 2017). In Ethiopia, hybrids give 27- 30% grain yield advantage over the open pollinated varieties and proved to be early maturing than their parental lines (Taye *et al.*, 2008; Hailu, 2012; Taye *et al.*, 2016).

Yield is a complex quantitative character and is greatly influenced by environmental fluctuations, hence, the selection of superior genotype based on yield *per se* at a single location in a year may not be very effective (Shrestha *et al.*, 2012). High and stable performance of crop under wider environmental conditions is a desirable attribute of cultivars. Information on the genotype by environment interaction leads to the successful evaluation of stable genotype; consequently, to select a cultivar with high yielding ability. Hence, high attention should be given to the importance of stability in performance for the genotypes under different environment and their interactions (Ghazy *et al.*, 2012).

Stability across environments is one of the most desirable properties of a genotype to be recommended for wide cultivation (Benti *et al.*, 1996). Stability usually refers to the genotypes ability to perform consistently over wide range of environments. To enhance superior and stable sorghum hybrid development information on nature and magnitude of genotype by environment interaction is extremely important. However, there is limited information on genotype by environment interaction and yield stability of *striga* resistant sorghum hybrids in Ethiopia. Therefore, the objectives of the study were to: Estimate the magnitude and nature of genotype by environment interaction for grain yield, and determine grain yield stability of *striga* resistant

sorghum hybrids in dry lowland areas of Ethiopia.

Materials and Methods

Description of the Study Sites

The field experiment was conducted in 2016 main cropping season in five locations representing the major sorghum growing dry lowland areas of Ethiopia (Figure 1), namely Fedis, Kobo, Mehoni, Sheraro and Humera research stations. They are found in East Hararghe zone (Oromia region), North Wello zone (Amhara region) and South, Northwest and West zones of Tigray region, respectively.

The agro-ecology of the locations are described as semi-arid belt of the eastern lowlands of Hararghe (Fedis), sub-moist hot warm low lands (Kobo, Mehoni and Sheraro) and hot to warm semiarid plain (Humera) sub agro-ecology (SA1-1) (EIAR, 2011) with a variation in elevation. The detailed agro-ecological features of the locations are presented in Table 1.

Table 1. Description of the study sites

Research stations	Geographic position			Rain Fall (mm)	Temperature (°C)		Soil type	Location code
	Altitude	Latitude	Longitude		Min	Max		
Humera	609	14° 06'N	39° 38'E	576.4	27.0	42.0	Vertisol	E1
Kobo	1468	12° 09'N	39° 38'E	673.4	15.36	30.24	Vertisol	E2
Fedis	1600	9° 07'N	42° 04'E	724.5	10.5	28.1	Alfisols	E3
Mehoni	1578	12° 41'N	39° 42'E	539.3	18.0	32	Vertisol	E4
Sheraro	1028	14° 24' N	37° 45' E	700	19.3	34.8	Vertisol	E5

Source: respective research centers, 2016

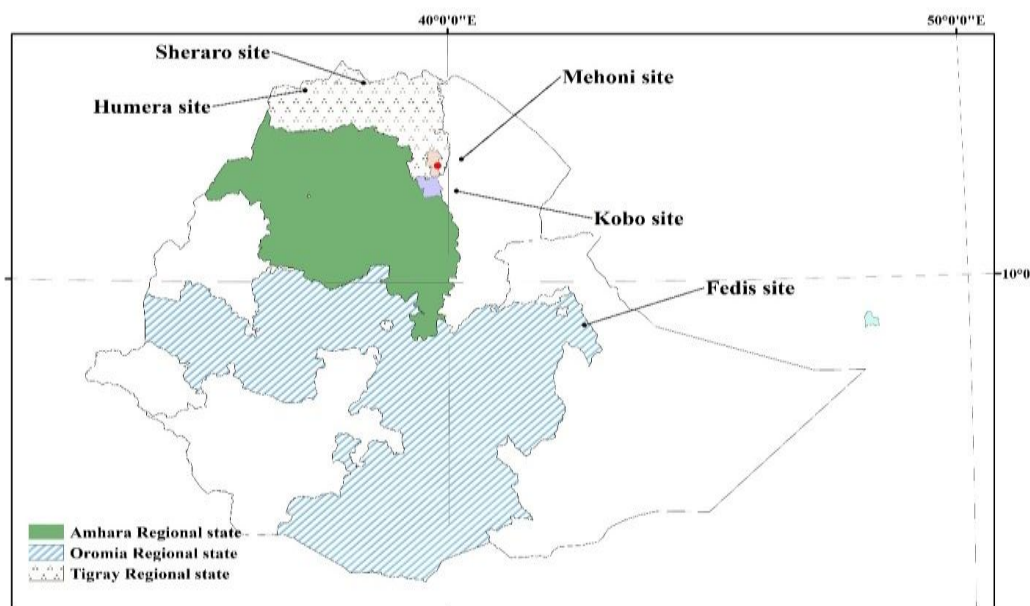


Figure 1. Map of the study sites

Planting Materials

The study comprised of 49 sorghum genotypes including three *striga* resistant check varieties, Goby (P9401), Abshir (P9403) and Birhan; two hybrids, ESH-1 and ESH-4 released by the national sorghum breeding program and 44 *striga* resistant sorghum hybrids introduced from Purdue University. The majority of the introduced hybrids were derived from the locally adapted *striga* resistant sorghum inbred lines with best performing seed parent developed at Purdue. The detailed information of the tested genotypes is presented in Table 2.

Table 2. Description of the experimental materials

SN	Genotypes	Pedigree	Code	Source
1	K7416	P140895A x P9401	G1	Purdue University
2	K7417	P140895A x P9405	G2	
3	K7418	P140895A x BRHAN	G3	
4	K7437	P140919A x P9401	G4	
5	K7438	P140919A x P9405	G5	
6	K7439	P140919A x BRHAN	G6	
7	K7445	P140927A x BRHAN	G7	
8	5136	P111535A x PSL985066	G8	
9	5151	P111539A x P9401	G9	
10	5152	P111539A x P9405	G10	
11	5153	P111539A x P9406	G11	
12	5155	P111539A x PSL985062	G12	
13	5156	P111539A x PSL985066	G13	
14	5160	P111539A x PSL985369	G14	
15	K7229	P111043A x P9401	G15	
16	K7230	P111045A x P9401	G16	
17	K7231	P111047A x P9401	G17	
18	K7232	P111051A x P9401	G18	
19	K7233	P111055A x P9401	G19	
20	K7234	P111073A x P9401	G20	
21	K7235	P111107A x P9401	G21	
22	K7236	P111125A x P9401	G22	
23	K7237	P111131A x P9401	G23	
24	K7242	P111163A x P9401	G24	
25	K7244	P111173A x P9401	G25	
26	K7245	P111183A x P9401	G26	
27	K7249	P111209A x P9401	G27	
28	K7251	P111225A x P9401	G28	
29	K7252	P111269A x P9401	G29	
30	K7255	P111339A x P9401	G30	
31	K7256	P111371A x P9401	G31	
32	K7259	P111021A x BRHAN	G32	
33	K7260	P111043A x BRHAN	G33	
34	K7263	P111051A x BRHAN	G34	
35	K7265	P111073A x BRHAN	G35	
36	K7266	P111107A x BRHAN	G36	
37	K7267	P111125A x BRHAN	G37	
38	K7268	P111131A x BRHAN	G38	
39	K7270	P111143A x BRHAN	G39	
40	K7273	P111163A x BRHAN	G40	
41	K7274	P111169A x BRHAN	G41	
42	K7276	P111183A x BRHAN	G42	
43	K7277	P111187A x BRHAN	G43	
44	K7280	P111209A x BRHAN	G44	
45	BRHAN	Check variety	G45	Melkassa Agricultural Research Center
46	GOBYE	Check variety	G46	
47	ABSHIR	Check variety	G47	
48	ESH-4	PU207 x PU304	G48	
49	ESH-1	P9401A x ICSR14	G49	

Experimental design and field management

The trial was laid out using a 7x7 simple lattice design with two replications in each location. Each plot consisted of two rows of 5 m length with 0.75 m and 0.20 m, between rows and plants, respectively. All plots were fertilized uniformly with 100 kg ha⁻¹ Di-ammonium Phosphate (DAP) and 50 kg ha⁻¹ Urea. Full dose of DAP and half of urea were applied at the time of planting and the remaining half was side dressed at knee height stage of the crop. All of the other agronomic management practices were applied as required at all locations as per the recommendations for sorghum in dry lowland areas of Ethiopia.

Data collection

Grain yield (kg ha⁻¹): It was adjusted to standard moisture level at 12.5% to get the grain yield per plot in grams and converted to kg ha⁻¹ for analysis.

Data analyses

Homogeneity of residual variances was tested prior to analysis over locations using Bartlett's tests (Steel and Torrie, 1980). Genotypes were assumed to be fixed and environment effects were treated as random. Mean separations for the treatment mean having significant differences at 5% probability levels was done using Duncan's Multiple

Range Test (DMRT) comparison procedure. The relative efficiency of the simple lattice design over randomized complete block design (RCBD) was checked and RCBD was found to be more efficient than that of the lattice design for grain yield. Analysis of variance for each environment, combined analysis of variance over environments, AMMI and GGE biplot analysis were computed using GenStat 16th edition software program.

Results and Discussion

Combined ANOVA across Environments for Grain Yield

The combined analysis of variance revealed that the genotype, environment and genotype × environment interaction were highly significant ($P \leq 0.001$). The total sum of square explained by the environment was 76.13% followed by genotype by environment interaction (12.66%) while the genotype explained the least (11.21%) (Table 3). The magnitude of the environment was 6.8 times greater than the genotype, implying that most of the variation in grain yield was due to the environment.

This result is in agreement with several findings (Asfaw, 2007; Abiy, 2015; Habte *et al.*, 2016; Kinde *et al.*, 2016) who reported that contribution of test environments are much greater than

the other sources of variation in most multi-environmental trials on sorghum. The significant genotype by environment interaction effects showed that genotypes responded differently to the variation in

environmental conditions of location which indicated the need for testing sorghum hybrids at multiple locations.

Table 3. Combined analysis of variance for grain yield of 49 sorghum genotypes evaluated at five environments in Ethiopia during 2016 cropping season

Source	DF	SS	MS	% explained
Reps. within Env.	5	2942779	588556	
Environment (E)	4	1167796816	291949204***	76.13
Genotype (G)	48	171888246	3581005***	11.21
GxE Interaction	192	194226843	1011598***	12.66
Error	240	58359242	243164	

***= significant at $P \leq 0.001$, DF = degree of freedom, SS = sum of square, MS = mean square

Mean Performance of Genotypes across Environments for Grain Yield

The mean grain yield of the tested genotypes showed ranking difference across the testing environments (Table 4). Thirty-two genotypes scored above the genotypic grand mean yield (2184 kg ha^{-1}); however, seventeen out of 49 genotypes had scored below genotypic mean yield, ranging from 735 kg ha^{-1} to 2179 kg ha^{-1} . The bold and underlined mean yields indicated in Table 4 are for those hybrids that were

the highest yielding in each environment. In comparison from the overall grand mean three of the testing environments, E1 (Humera), E2 (Kobo) and E3 (Fedis) had the lower mean grain yield, while two of the testing environments, E4 (Mehoni) and E5 (Sheraro) scored the higher mean grain yield. The large variation of locations on grain yield might be due to the difference in total amount of rain fall at different growing stages, various edaphic, climatic and biotic factors.

Table 4. Mean grain yield (kg ha⁻¹) of 49 sorghum genotypes evaluated at five environments in Ethiopia during 2016 cropping season

Genotypes	Testing Environments					GM
	Humera	Kobo	Fedis	Mehoni	Sheraro	
G1	670 ^{d-i}	1007 ^{d-m}	1548 ^{c-j}	5001 ^{b-e}	5233 ^{a-j}	2692 ^{b-f}
G10	693 ^{d-h}	384 ^{no}	651 ^{l-o}	1533 ^{q-t}	1740 ^{op}	1000 ^{pq}
G11	425 ^{h-l}	165 ^o	400 ^{no}	1400 ^{rst}	2266 ^{n-p}	932 ^{pq}
G12	797 ^{c-f}	615 ^o	1086 ^{g-n}	2684 ^{i-s}	2620 ^{m-o}	1561 ^{m-o}
G13	1069 ^{abc}	409 ^{no}	741 ^{k-o}	1667 ^{p-t}	1906 ^{op}	1159 ^{o-q}
G14	548 ^{e-l}	211 ^o	327 ^o	2001 ^{o-t}	1100 ^p	838 ^q
G15	780 ^{c-g}	1037 ^{c-l}	1841 ^{b-f}	2267 ^{l-t}	5320 ^{a-j}	2249 ^{e-j}
G16	671 ^{d-i}	824 ^{g-n}	2408 ^{ab}	4468 ^{b-j}	4920 ^{b-k}	2658 ^{b-f}
G17	307 ^{kl}	1178 ^{a-j}	998 ^{i-o}	3932 ^{c-l}	4840 ^{b-l}	2251 ^{e-i}
G18	1075 ^{abc}	1348 ^{a-g}	1273 ^{f-l}	4534 ^{b-h}	4886 ^{b-k}	2623 ^{b-f}
G19	510 ^{f-l}	1178 ^{a-j}	830 ^{j-o}	3335 ^{e-p}	6426^a	2456 ^{c-g}
G2	635 ^{e-j}	697 ^{h-o}	976 ^{i-o}	3733 ^{c-m}	3448 ^{l-n}	1898 ^{h-m}
G20	541 ^{e-l}	1435 ^{a-f}	1737 ^{b-g}	5468 ^{abc}	5286 ^{a-j}	2894 ^{abc}
G21	332 ^{kl}	1361 ^{a-g}	2060 ^{bcd}	4467 ^{b-i}	5920 ^{a-d}	2828 ^{a-d}
G22	330 ^{kl}	1108 ^{b-j}	1720 ^{b-h}	4268 ^{b-j}	5833 ^{a-e}	2652 ^{b-f}
G23	391 ^{h-l}	888 ^{f-n}	1225 ^{f-l}	3602 ^{d-o}	4766 ^{c-l}	2175 ^{e-l}
G24	343 ^l	1197 ^{a-j}	1825 ^{b-f}	4801 ^{b-g}	5227 ^{a-j}	2679 ^{b-f}
G25	668 ^{e-k}	842 ^{g-n}	1436 ^{c-k}	4933 ^{b-f}	4173 ^{h-l}	2410 ^{c-h}
G26	856 ^{b-e}	644 ^{i-o}	1427 ^{d-k}	4034 ^{c-k}	4407 ^{e-l}	2274 ^{e-h}
G27	1089 ^{abc}	1076 ^{c-k}	1274 ^{f-l}	3066 ^{g-r}	5007 ^{b-k}	2303 ^{d-h}
G28	871 ^{b-e}	1489 ^{a-e}	1821 ^{b-f}	2933 ^{h-r}	5720 ^{a-g}	2567 ^{b-g}
G29	515 ^{f-l}	1732^a	1821 ^{b-f}	5000 ^{b-e}	6187 ^{abc}	3051 ^{ab}
G3	441 ^{h-l}	866 ^{f-n}	1091 ^{g-n}	4000 ^{c-l}	4820 ^{b-l}	2244 ^{e-k}
G31	316 ^{kl}	1369 ^{a-g}	1102 ^{g-n}	3599 ^{d-o}	4600 ^{d-l}	2197 ^{e-k}
G32	643 ^{e-j}	1587 ^{a-d}	931 ^{i-o}	3334 ^{e-p}	5386 ^{a-i}	2377 ^{c-h}
G33	448 ^{g-l}	618 ^{j-o}	1128 ^{f-m}	3133 ^{g-q}	5533 ^{a-h}	2172 ^{e-l}
G34	283 ^{kl}	891 ^{f-n}	1290 ^{f-l}	4367 ^{b-j}	5720 ^{a-g}	2510 ^{c-g}
G35	469 ^{f-l}	1307 ^{a-g}	1795 ^{b-g}	2734 ^{i-s}	3893 ^{kl}	2040 ^{g-m}
G36	296 ^{kl}	1362 ^{a-g}	1606 ^{c-i}	4101 ^{b-k}	4926 ^{b-k}	2458 ^{c-g}
G37	385 ^{h-l}	470 ^{l-o}	967 ^{i-o}	4000 ^{c-l}	5073 ^{a-k}	2179 ^{e-l}
G38	684 ^{d-h}	1678 ^{ab}	1017 ^{h-o}	3799 ^{c-l}	4347 ^{f-l}	2305 ^{d-h}
G39	617 ^{e-k}	1321 ^{a-g}	1431 ^{d-k}	3933 ^{c-l}	4566 ^{d-l}	2374 ^{c-h}
G4	444 ^{h-l}	831 ^{g-n}	2887^a	4467 ^{b-i}	4933 ^{b-k}	2713 ^{b-f}
G40	342 ^{ijkl}	1484 ^{a-e}	1189 ^{f-m}	5800 ^{ab}	4813 ^{b-l}	2726 ^{b-f}
G41	1030 ^{abc}	1157 ^{a-j}	1177 ^{f-m}	3733 ^{c-n}	4673 ^{d-l}	2354 ^{c-h}
G42	462 ^{g-l}	1214 ^{a-i}	979 ^{i-o}	3002 ^{h-r}	5633 ^{a-g}	2258 ^{e-h}
G43	980 ^{bcd}	1601 ^{abc}	1196 ^{f-m}	3667 ^{d-o}	4160 ^{h-l}	2321 ^{d-h}
G44	495 ^{f-l}	1135 ^{b-j}	1088 ^{g-n}	3266 ^{e-p}	5773 ^{a-f}	2352 ^{c-h}
G45	643 ^{e-j}	1180 ^{a-j}	1202 ^{f-m}	1665 ^{p-t}	3673 ^{k-m}	1673 ^{l-n}
G46	561 ^{e-l}	962 ^{e-n}	981 ^{i-o}	2001 ^{m-t}	4087 ^l	1718 ⁱ⁻ⁿ
G47	286 ^{kl}	910 ^{e-n}	1313 ^{e-l}	2466 ^{k-t}	4520 ^{d-l}	1890 ^{h-m}
G48	286 ^{kl}	493 ^{k-o}	504 ^{m-o}	1533 ^{q-t}	3947 ^{kl}	1353 ^{n-p}
G49	437 ^{h-l}	1250 ^{a-h}	1834 ^{b-f}	6667^a	6200 ^{ab}	3278^a
G5	1146 ^{ab}	794 ^{g-n}	1381 ^{d-k}	3200 ^{f-q}	4326 ^{g-l}	2170 ^{f-l}
G6	1321^a	996 ^{e-m}	2137 ^{bc}	4467 ^{b-i}	4740 ^{d-l}	2732 ^{b-e}
G7	585 ^{e-l}	862 ^{f-n}	2003 ^{b-e}	5267 ^{a-d}	4533 ^{d-l}	2650 ^{b-f}
G8	263 ^l	430 ^{m-o}	399 ^{no}	866 ^t	1713 ^{op}	735 ^q
G9	341 ^l	205 ^o	998 ^{i-o}	1067 st	1680 ^{op}	858 ^q
EM	588	985	1319	3518	4508	2184
CV (%)	23.2	24.3	22	20.1	12.8	20.4

Where: GM=Genotypic means, EM=Environment means; CV (%) = Coefficient of variation in percent and values with the same letters in a column are not significantly different at P ≤ 0.05.

Stability analysis based on additive main effects and multiplicative interaction (AMMI) model

The result for the additive main effects and multiplicative interaction (AMMI) model is presented in Table 5. The AMMI analysis of variance for grain yield (kg ha^{-1}) showed that the mean squares for genotypes, environments and GEI were highly significant ($P \leq 0.001$). The larger sum of square and highly significant mean squares of environments for grain yield indicated that the environments were diverse, which is in agreement with the previous findings of Alberts (2004); Solomon *et al.* (2008); Abdurahman (2009) on maize and Gezahegn *et al.* (2017) on napier grass.

The significant genotype by environment interaction effect was further partitioned in to two interaction principal component axis (IPCA). The results of AMMI analysis showed highly significant ($P \leq 0.001$) differences for the first two interaction principal component axis (IPCA). The first interaction principal component (IPCA1) captured 62.46% and the second (IPCA2) further explained 27.71% and the two interaction principal components cumulatively explained 90.20% of the genotype by environment interaction sum of square and the rest 9.80% was contributed due to noise.

Based on Gollob (1968) the two interaction principal components were

significant ($P \leq 0.001$) while the IPCA3 was non-significant. Therefore, the AMMI-1 with only two interaction principal component axis was the best predictive model for grain yield. This is in harmony with Zobel *et al.* (1988) and Annicchiarico (2002). The third interaction principal component axis captured mostly noise and did not help to predict valid observations. Hence, the interaction of the 49 genotypes with five environments was best predicted by the two interaction principal components. In general, factors like type of crop, diversity of the genotype and range of environmental conditions affect the degree of complexity of the best predictive model (Crossa, 1990).

Genotypes selection by AMMI model

Multi-location trials are very important for selecting the best genotype for wide or specific environments before any recommendation of genotypes for future commercial production. The four best hybrids selected by AMMI model for each environment are presented in Table 6. In this study, genotypes were reacted differently to environmental fluctuation (have high GEI), as a result the best AMMI model allows as to select relatively better genotypes that suit to a specific environment. The positive and negative IPCA-1 scores revealed favorable and unfavorable environments. Thus, Sheraro and Mehoni had a positive IPCA-1 score and high mean yield in the favorable environments. On the contrary, Humera, Kobo and Fedis had negative IPCA-1 score and low mean yield below the grand mean in the unfavorable environments.

Table 5. Additive main effects and multiplicative interaction (AMMI) analysis of variance for grain yield (kg ha⁻¹) of 49 sorghum genotypes evaluated at five environments in Ethiopia during 2016 cropping season.

Source	DF	SS	MS	Sum of squares % explained		
				Total	GEI	GEI Cmu.
Reps. within env.	5	2942779	588556 ^{ns}			
Environment (E)	4	1167796816	291949204 ^{***}	76.13		
Genotype (G)	48	171888246	3581005 ^{***}	11.21		
GxE Interaction	192	194226843	1011598 ^{***}	12.66		
IPCA 1	51	121313805	2378702 ^{***}		62.46	62.46
IPCA 2	49	53825505	1098480 ^{***}		27.71	90.20
IPCA 3	47	13061480	277904 ^{ns}		0.27	
Residuals	45	6026054	133912 ^{ns}			
Pooled error	240	58359242	243164			
Total	489	1595213927				

Key: ***= significant at P-value ≤ 0.001 and ns = non-significant, IPCA=interaction principal component axis, GEI = Genotype by Environment Interaction explained and GEI cum. = GEI cumulative, SS=Sum of Squares, MS= Mean Square.

Accordingly, genotype G49 was the best for high yielding environments of Mehoni and Sheraro and genotypes G19 and G4 were specifically adapted to Sheraro and Fedis (Table 6). G29, G20 and G21 performed better in the high yielding to low yielding environments and thus stable across environments, whereas G6 was the

best genotype for low to medium yielding environments of Humera and Fedis. The other hybrids that were selected did not show a distinct pattern of adaptation and more specific adapted either lower or higher yielding environments.

Table 6. The AMMI model's best four sorghum hybrids selection for grain yield per environment

Environment	Sites	Mean	IPCA 1 Score	The first four AMMI selected hybrids			
				1	2	3	4
E5	Sheraro	4508	47.19	G19	G49	G29	G21
E4	Mehoni	3518	46.89	G49	G40	G20	G7
E3	Fedis	1319	-21.09	G4	G16	G6	G21
E2	Kobo	985	-25.23	G29	G38	G43	G32
E1	Humera	588	-47.76	G6	G5	G27	G18

GGE Biplot Analysis

In the AMMI model, only the GEI term is absorbed, whereas in the GGE model, the main effects of genotypes (G) plus the GEI, are the two sources of variation of GGE biplot. In GGE biplot, the best genotype is the one with large PC1 scores (high mean yield) and near zero PC2 scores (high stability). In this study PC1 and PC2

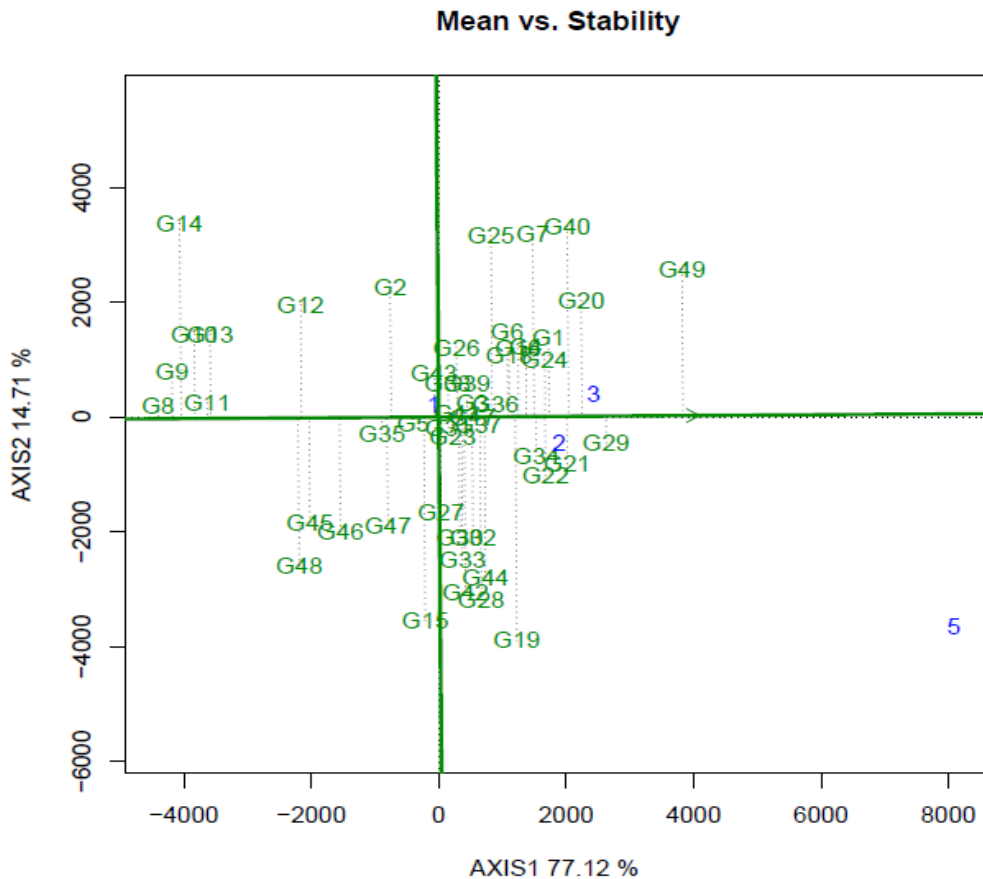
accounted for 77.12% and 14.71% of the total GGE (genotype and genotype by environment interaction), respectively, and a total of 91.83% of GGE. GGE biplot was used to identify mega environments, genotype and environment evaluation, stability of genotypes and identification of ideal genotype and environments.

Mean Performance and Stability of Genotypes

The graphical method for mean performance and stability analysis of genotypes is presented in Figure 2. It was based on row metric preserving where the singular values were entirely partitioned into genotype scores. For this procedure, single arrowed line that passes through the biplot origin and points to higher mean yield across environments was drawn. This line is called the average environment coordination (AEC) abscissa and labeled as AEA. The arrow directs towards higher average yield and hence genotypes on the right side most of this line have highest average yield. Single arrowed line that is perpendicular to AEC abscissa was also drawn and this line is called the AEC ordinate and is labeled as Perpendicular Line (PL). This line

points towards greater variability in either direction and hence genotype that has longer vector along this line is highly unstable (Ilker *et al.*, 2011).

The shorter the genotype vector is the more stable than others. Thus, among the tested genotypes G29, G21, G22, G24 and G34 were identified as high yielder and stable genotypes while G14, G12, G2, G15, G48, G28, G42 and G19 were found to have lower mean grain yield with longer vector length and identified as the most unstable genotypes across the test environments, which is in agreement with the previous findings of Habte *et al.* (2016) in sorghum, Demissew *et al.* (2016) in quality protein maize hybrids; Dejene (2016) in bread wheat and Fantaye *et al.* (2018) on sesame.



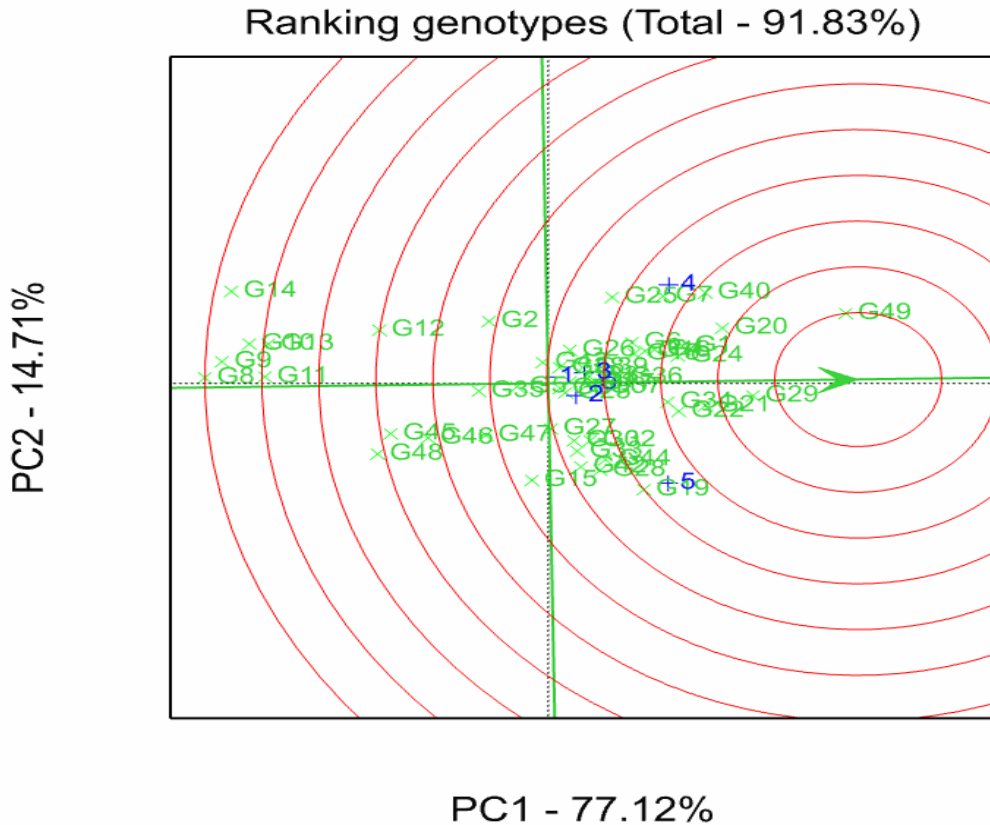
Where E1 refers to Humera, E2= Kobo, E3 =Fedis, E4= Mehoni, E5=Sheraro

Figure 2. The mean performance and stability view of the GGE biplot of 49 sorghum genotypes at five environments

Ranking Genotypes Relative to the Ideal Genotype

GGE biplot based on ranking of genotypes relative to the ideal genotype for grain yield is presented (center of the concentric circle) in Figure 3. According to this ranking procedure, the genotypes closer to the ideal genotype are stable, while genotypes far from the ideal genotypes were the unstable. G49 followed by G29 were the “ideal” genotype with high mean grain yield and closer to the small circle being located on the AEC

abscissa and with an arrow pointing to it (Fig. 4). Genotype is more desirable if it is located closer to the ideal genotype. Therefore, G21, G22, G34 and G24 were plotted closer or near to the ideal genotype and considered as the most desirable and stable genotypes, while G40 and G20 were high yielding genotypes associated with genotypic instability. Similar results were reported by various authors (Habte *et al.*, 2016; Farshadfar *et al.*, 2012; Mitrovic *et al.*, 2012; Yirga, 2016; Fantaye *et al.*, 2018).



Key: E1 =Humera, 2= Kobo, 3 =Fedis, 4= Mehoni, 5=Sheraro
 Figure 3. GGE-biplot showing the "ideal" sorghum genotype

Relationship among environments

The relationship among testers is graphically described in Figure 4. Further information about the discriminating power of environments, together with a representation of their mutual relationships, can be obtained by then environment-vector view of the GGE-biplot. In this case, a long environmental vector reflects a high capacity to discriminate the genotypes. The cosine of the angle between two environments is used to approximate the correlation between them as described and used in Kaya *et al.*

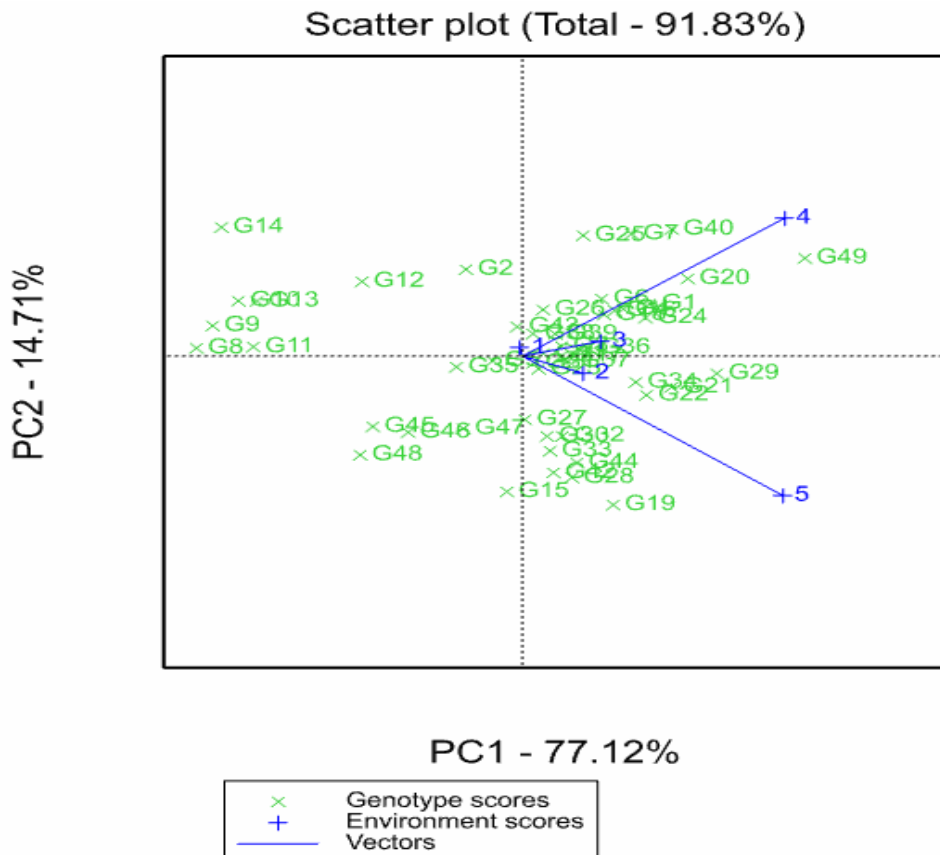
(2006) and Dehghani *et al.* (2010) and a wide obtuse angle ($>90^\circ$) indicates a strong negative correlation, an acute angle ($<90^\circ$) indicates a positive correlation while a close-to- 90° angle indicates lack of correlation (Yan and Tinker, 2006).

According to the angles of test location vectors, the five locations are grouped into three major groups. The first group Sheraro and Kobo was closely correlated (Figure.5) suggesting that the locations provide redundant information about genotypes; the second group includes Mehoni and Fedis, while the other

group involves Humera. The smallest angle is between environments Sheraro and Kobo, implying that there is highest correlation between them. The angle between Humera and Mehoni, Humera and Sheraro are greater than 90° , showing a negative correlation between them. Whereas, the angle between Humera and Kobo, Humera and Fedis is equal to 90° , indicating little or no correlation between these environments. The angle between Mehoni and Fedis, Mehoni and Kobo, Mehoni and Sheraro, Fedis and Kobo, Fedis and

Sheraro are less than 90° indicating there is the correlation between these locations.

Obtaining suitable tool to analyze this kind of similar information by using fewer test environments generally reduces the cost of testing and increases breeding efficiency. With the longest vectors from the origin, environments Mehoni and Sheraro were the most discriminating. Fedis and Kobo were moderately discriminating while Humera was least discriminating.



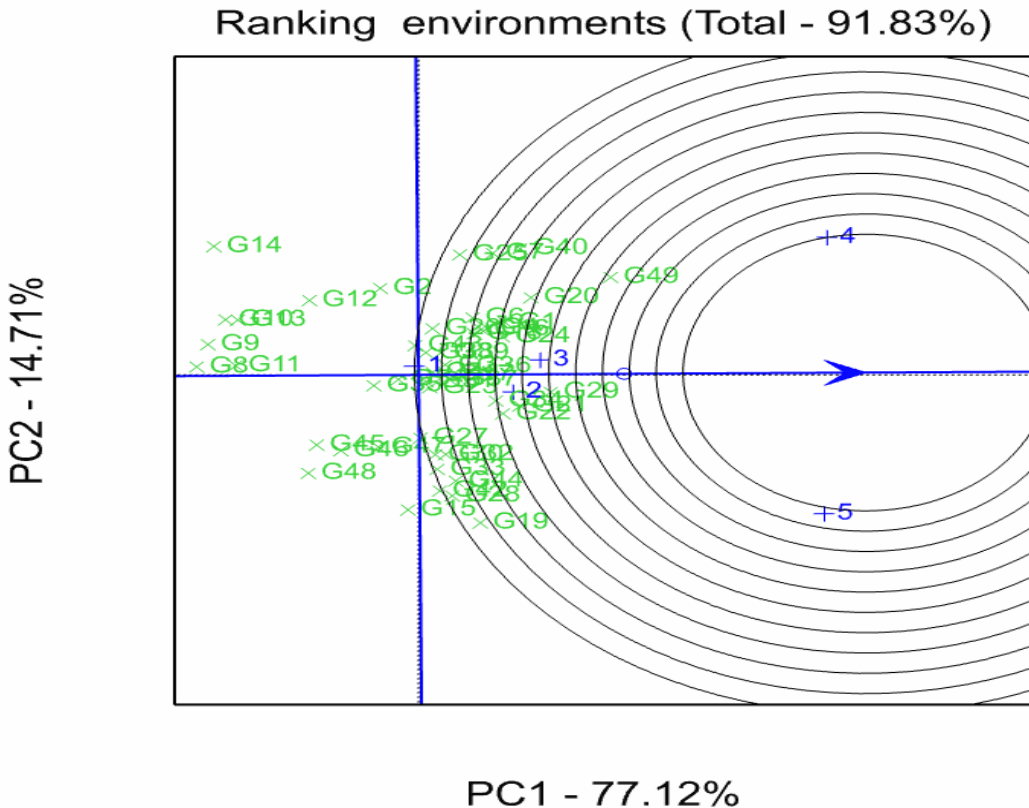
Key: E1=Humera, 2=Kobo, 3=Fedis, 4= Mehoni, 5=Sheraro

Figure 4. GGE-biplot showing the "ideal" environment

Ranking Environments Relative to the Ideal Environment

Similarly to the ideal genotype, the ideal environment is located in the first concentric circle in the environment-focused biplot as shown Figure 5. Desirable environments are close to the ideal environment. Accordingly,

nearest to the first concentric circle, the environment Mehoni followed by Sheraro was the ideal environments to select widely adapted sorghum genotypes, whereas, Humera, Kobo and Fedis were not an ideal environment.



Key: Where 1 = Humera, 2 = Kobo, 3 = Fedis, 4 = Mehoni, 5 = Sheraro.

Figure 5. GGE-biplot showing the "ideal" environment

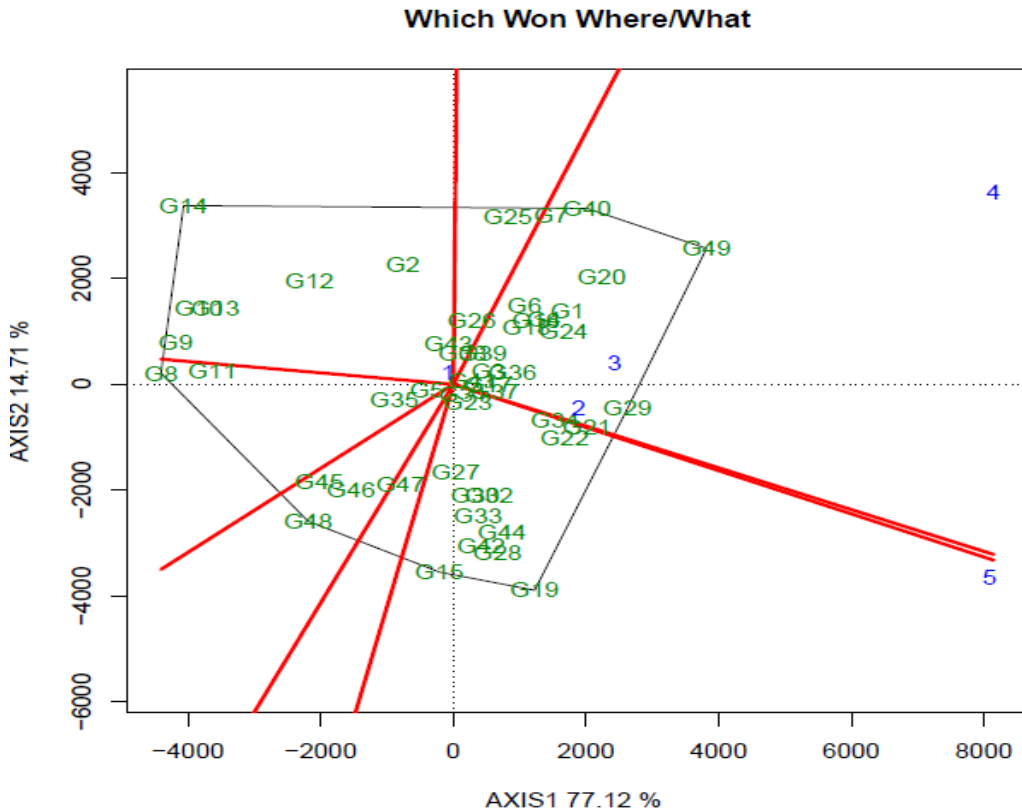
'Which-Won-Where' Pattern and Mega- environment Identification

The polygon in Figure 6 is formed by connecting the markers of the

genotypes that are further away from the biplot origin such that all other genotypes are contained in the polygon. One of the most important properties of GGE biplot is its ability to show the which-won-where pattern

and mega environment differentiation from the genotype by environment interaction and hence is a concise summary of the $G \times E$ pattern of a multi environment trials data set (Yan, 2002). Mega environment is a group (cluster) of locations or environments that constantly share the same best/winning genotype. Genotype evaluation within a mega-environment should, therefore, be based on both mean performance and stability to avoid the random GEI. This could be done by identifying the ideal genotype. The testing environments (Figure 6) fell into seven sectors with different winner genotypes and the biplot showed that six vertex genotypes, G8, G14, G19, G40, G48 and G49. According to Yan and Kang (2003) genotypes located on the vertices of the polygon performed either the best or the poorest in one or more environments.

Therefore, the GGE biplot graph identified two different sorghum growing mega-environments for grain yield. The first environment includes higher yielding E4 (Mehoni) to lower yielding E1 (Humera), E2 (Kobo) and E3 (Fedis) environments, with the winner genotype G49; the second environment containing the highest yielding environment (E5) in Sheraro area with winner genotype G19 presented in Figure 7. On the contrary, the result also showed some genotypes which fell in sectors where there were no locations at all; these genotypes are poorly adapted to five of the testing locations (G2, G3, G5, G9, G10, G12, G35, G45, G46 and G47). Gasura *et al.* (2015), Habte *et al.* (2016) and Al-Naggar *et al.* (2018) are among the many authors who used GGE bi-plot to identify mega environments, to evaluate the genotypes and to test the environments in sorghum.



Key: E1 =Humera, 2= Kobo, 3 =Fedis, 4= Mehoni, 5=Sheraro

Figure 6. Polygon view of GGE biplot graph for which-won-where (mega environment) pattern of GEI for grain yield.

Conclusion and Recommendation

This study revealed highly significant ($P \leq 0.001$) difference among environment (E), genotype (G) and genotype $\times$ environment interaction (GEI). Environment explained 76.13% of the total ($G + E + GE$) variation, whereas, G and GE explained 11.21% and 12.66% of the total variation, respectively. Based on the combined analysis of variance over locations, the mean grain yield of environments ranged from 588 kg ha^{-1} in Humera to 4508 kg ha^{-1} in Sheraro. The highest yield was obtained from ESH-1 (3278 kg ha^{-1}), while the lowest was from

K5136 (735 kg ha^{-1}) and the average grain yield of genotypes was 2184 kg ha^{-1} . The results of AMMI analysis showed highly significant ($P \leq 0.001$) differences for the first two interaction principal component axis (IPCA) where IPCA1 captured 62.46% and IPCA2 further explained 27.71% of the genotype by environment interaction sum of square and the rest 9.80% was contributed due to noise. Based on AMMI model, K7439, K7252 and K7437 were specifically adapted to low environments of Humera, Kobo and Fedis, whereas, ESH-1 and K7233 were the better

hybrids for favorable environments of Mehoni and Sheraro, respectively.

Based on the GGE biplot analysis different sorghum growing environments were grouped in to two: The first environment includes higher E4 (Mehoni) to low yielding E1 (Humera), E2 (Kobo) and E3 (Fedis) environments, respectively with the winner genotype ESH-1. The second environment contained the highest yielding environment (E5) in Sheraro area with winner genotype K7233. Thus, the which-won-where biplot showed two winning genotypes in two mega environments. However, the standard hybrid check, ESH-1 won in most of the environments. Therefore, ESH-1 can be recommended for wider cultivation due to better grain yield and stability performance across the test environments in the dry lowland areas of Ethiopia.

Acknowledgments

The authors acknowledge financial support by Tigray Agriculture Research Institute (TARI) in collaboration with Integrated Striga Control Project. We are grateful to the National Sorghum Breeding Program of Ethiopia in partnership with the US Principal Investigator (Prof. Gebisa Ejeta) for the research facilities and supplying germplasm (breeding materials) used in the study.

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The Release and Registration of *Bako-09* (Acc. 214995) Finger millet Variety

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Abstract

The name Bako-09 was given to the finger millet (*Eleusine coracana* sub spp. *coracana*) variety with the pedigree of Acc. 214995, which was introduced from Zambia through Ethiopian Biodiversity Institute and released as a variety by Bako Agricultural Research Center in 2017. Bako 09 and the other eleven pipeline genotypes were evaluated against standard check (Gute) at Bako and Gute sites from 2013 to 2015 and at Boneya Boshe in 2014 main cropping season. Additive main effect and Multiplicative Interaction (AMMI), Genotype and Genotype by Environment interaction (GGE) biplot analysis, and Eberhart and Russell regression model revealed that Bako 09 is stable and high yielding (2.99 t ha⁻¹) with a yield advantage of 21.99% over the standard check. Besides, the variety has purple leaf, nodes and finger color, which is a known trait for its resistance to diseases and dominant over green the other colored traits in finger millet. Therefore, Bako-09 was released in 2017 for its high grain yield potential and moderately resistant against *Magnaporthe oryzae* disease.

Keyword: AMMI, Finger millet (*Eleusine coracana* subsp. *coracana*), GGE biplot, *Magnaporthe oryzae*

Introduction

Finger millet (*E. coracana* subsp. *coracana*, 2n=4x=36), is the most important subsistence crop of Africa and India (Babu *et al.*, 2007). It is potentially a climate-resilient and nutritious crop with highly nutritious and antioxidant properties (Kumar *et al.*, 2017). Very importantly, finger millet grain is gluten-free, rich in calcium, fiber, iron, and has excellent malting qualities (Chandrashekar, 2010 and Pradhan *et al.*, 2010). The

major positive traits of finger millet is its adaptability to adverse agro-ecological conditions with minimal inputs, tolerant to moisture stress, produced on marginal land where other crops cannot perform and tolerant to acidic soil (Upadhyaya *et al.*, 2007).

Despite its wider production coverage and immense nutritional importance, limited availability of stable high yielding and disease tolerant finger millet variety is one of the major production constraints in Ethiopia.

Therefore, the primary objective of this study was to develop adaptable, high yielding, stable and disease tolerant finger millet varieties for the test environments and similar agroecologies of the country.

Varietal Origin and Evaluation

Bako-09 (Acc. 214995) finger millet variety was originally introduced from Zambia through Ethiopian Institute of Bio-diversity (IBC). The *Bako-09* and other pipeline varieties were evaluated against the standard check, Gute, for three consecutive years (2013-2015) at Bako and Gute and in 2014 at Boneya Boshe research stations.

Agronomic and Morphological characteristics

Bako-09 (Acc. 214995) is characterized by purple pigmented leaves, nodes and finger with brown seed color. Purple pigmented types of finger millet are more resistant to blast than non-pigmented ones and is dominant over green (Kenneth and LeRoy, 1977). The average 1000 seeds weight was 2.6 grams, and its average plant height was 88.8cm. The detailed agronomic characteristics of the variety is indicated in Table 2 below.

Yield Performance

The released variety Bako-09 showed higher mean grain yield (2.99 t ha^{-1}) and more stable performance with yield advantage of 21.99% over the standard check, Gute (Table 1).

Table 1: Mean seed yield (ton ha^{-1}) of 11 finger millet genotypes tested in seven environments.

Genotype	Mean grain yield (ton ha^{-1})							Mean
	Bako			Gute			B. Boshe	
	2013	2014	2015	2013	2014	2015	2014	
214995	3.85	3.18	3.69	3.04	3.08	1.78	2.31	2.99
BKFM0058	2.79	2.00	4.04	1.72	3.26	2.04	1.74	2.51
BKFM0052	3.18	1.93	4.05	2.32	3.10	1.89	1.25	2.53
203547	3.79	2.64	3.29	2.33	2.93	1.75	1.33	2.58
229727	3.58	2.45	2.99	2.60	2.92	2.53	2.60	2.81
BKFM0063	3.67	2.24	4.14	2.20	2.98	1.54	2.17	2.70
203356	2.73	2.04	2.50	1.99	2.48	1.87	1.25	2.12
203351	3.09	2.31	2.93	3.10	2.86	1.98	1.85	2.59
BRCFM-8-04	3.19	2.29	3.23	1.79	2.79	1.93	1.22	2.35
Anno-1	2.64	2.01	3.73	2.15	2.16	1.67	1.43	2.26
Gute	2.56	2.78	3.32	2.62	2.93	1.69	1.26	2.45
Mean	3.19	2.35	3.4	2.35	2.86	1.88	1.67	2.54
CV (%)	10.8	9.3	5	19.9	11.2	19.7	15.2	
F- Value	**	**	Ns	*	**	Ns	**	

CV=coefficient of variation, ** highly significant, * significant

Table 2. Agronomic/morphological characteristics of finger millet variety Bako 09

Variety name and pedigree	Bako 09 (Acc. 214995)
Adaptation area	Bako, Gute, B/Boshe and similar agro-ecologies
Adaptation area:	Altitude(mal): 1400-2300m
	Rainfall (mm): 1200-1300mm
Average Days to flowering	84 days
Average Days to maturity	146 days
1000 seed weight (g)	2.6
Mean Plant height (cm):	89
Seed color	Brown
Growth habit	Erect
Grain yield (ton/ha)	
On farmers field:	2.3-2.57
On station:	2.34-2.98
Blast disease reaction	Moderately resistant
Year of release	2017
Breeder/Maintainer	Bako Agricultural Research Center (BARC/OARI)

Stability and Adaptability Performance

Eberhart and Russell (1966) model revealed that *Bako-09* (Acc. 214995) showed regression coefficient (bi) relatively closer to unity (0.9879) and reasonably acceptable deviation from regression that approaches to zero (0.0321), implying the variety is stable and widely adaptable than the other genotypes (Table 3). GGE biplot analysis also showed that Bako-09 (Acc 214995) fall in the central circle away from vertical mean line and closer to the origin, indicating its high yield potential and relative stability

compared to the other genotypes (Fig 1). Similarly, the AMMI analysis result revealed that Acc. 214995 and BKFM0063 recorded IPCA values relatively close to zero and hence are better stable and widely adaptable genotypes across locations.

Reaction to Major Diseases

Bako-09 (Acc.214995) showed moderately tolerant to blast (*Magnaporthe oryzae*), which is the major bottleneck for finger millet production in western Oromia.

Table 3: Regression coefficient (bi) and squared deviation from linearity of regression (s2di) by the test genotypes revealed using Eberhart and Russell model.

Genotypes	Regression coefficient (bi)	Squared deviations from regression (S ² di)	Grain yield (tons ha ⁻¹)
214995	0.9879	0.0321	2.99
BKFM0058	1.0460	0.0125	2.51
BKFM0052	0.9459	0.0607	2.53
203547	1.1639	0.1244	2.58
229727	0.4471	-0.0233	2.81
BKFM0063	1.2289	-0.0113	2.70
203356	1.4084	-0.0342	2.12
203351	1.3174	0.0292	2.59
BRCFM-8-04	0.6978	-0.0574	2.35
Anno-1	0.6600	0.0095	2.26
Gute	1.0966	-0.0407	2.45

Standard error of beta = 0.2074; t = Tons; ha = Hectare; *, ** = Significant at $P < 0.05$ and $P < 0.01$ levels, respectively.

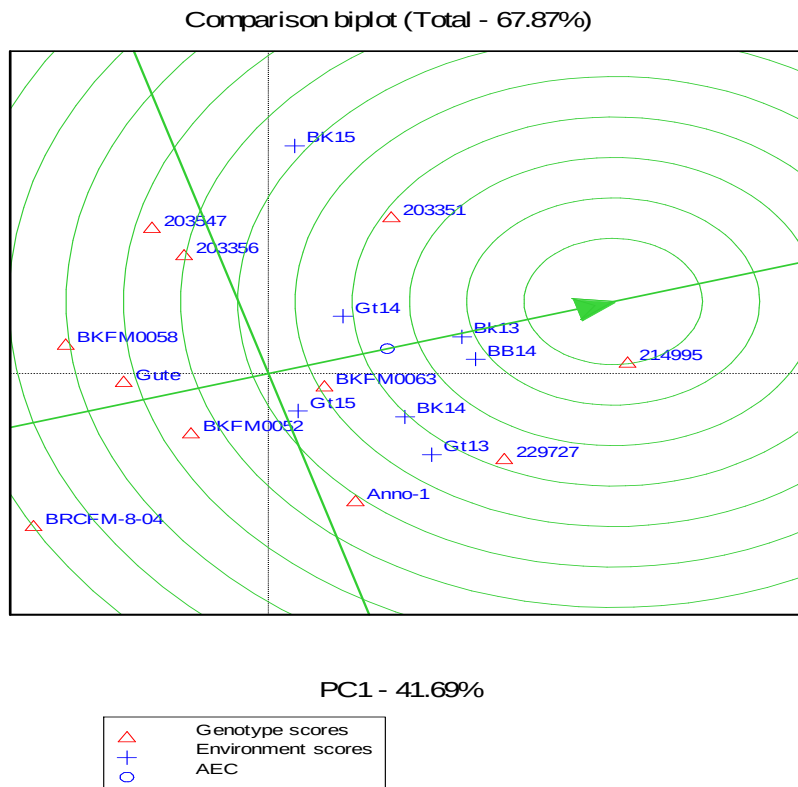


Fig 1: GGE Biplot analysis showing grain yield stability of tested genotypes and environments

Conclusion

Bako-09 gave high grain yield, showed wider adaptability, tolerant to blast and stable performance than the standard check and other tested genotypes. Therefore, smallholder farmers and other finger millet producers inhabiting around Bako, Boneya Boshe, Gute and areas with similar agro-ecology can grow Bako-09 variety with its full agronomic and other management recommendations.

Acknowledgments

The authors would like to thank Oromia Agricultural Research Institute for funding the research. Staff members of Bako Agricultural Research Center in general and Cereal Crops Technology Generation Team in particular are highly acknowledged for their support in field work.

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The Release and Registration of Gute (Late Set) Soybean Varieties

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Abstract

Gute is the name given to soybean [*Glycine max* (L.) Merr.] variety with pedigree of PM 12-3, brought from Jimma Agricultural Research Center. *Gute* variety was evaluated against the check and other genotypes for seed yield, agronomic characters and disease reaction at Bako, Billo Boshe and *Gute* experimental sites from 2016/2017 to 2017/2018. *Gute* variety was verified for possible release in 2019 at on farm and on station across all locations listed above. *Gute* gave seed yield of 2779.1 kg ha⁻¹, 39.4% protein content and 22.3% oil content respectively. The result of multi-environment yield trials showed that *Gute* (PM 12-3) outperformed the standard check (PRAC-3) by 20.1 % in seed yield and comparable in oil content. It was resistant to bacterial blight and bacterial pustule. Stability analysis showed that the variety was relatively stable in grain yield performance across locations than the check variety PARC-3. Therefore, *Gute* was released in 2020 for its high grain yield potential, disease tolerance and farmers preferences, and recommended for wider production in the test environments and similar agro-ecologies

Keywords: Commercial Variety, Pedigree, Soybean, Stability

Introduction

Soybean [*Glycine max* (L.) Merr.] is a legume native to East Asia perhaps in North and Central China (Laswai *et al.*, 2005) and it is grown for edible bean, oil and protein around the world. Soybean is found in family *Fabaceae* and species *G. max* (Shurtleff and Aoyagi, 2007). Soybean is one of the most important oil grain legume crops in the world. In the International trade market, soybean ranks number one among the major oil crops with an average protein content of 40% on dry matter basis. It has the highest protein content of all field crops and is the

second only to groundnut in terms of oil content (20%) among the food legumes. Dugje *et al.* (2009) reported that soybean is more protein rich than any of the common vegetable or legume food sources in Africa. Soybean is a promising pulse crop proposed for alleviation of acute shortage of protein and oil worldwide (Mahamood *et al.*, 2009). Soybean production begins only recently in Africa, during the second half of 20th century, is believed introduced to Ethiopia in the 1950's. Soybean research was started in the 1970's. Since then, 25 soybean varieties have been released in Ethiopia. Soybean

was the leading oil crop next to palm with over 250 million metric ton production in 2013 (FAO, 2014). It is rich sources of protein (38-46%) and oil (18-20%). Soybean containing 2.5 times the protein contents of wheat and four times the protein contents of maize. Soybean is classified in different groups such as early, medium and late maturing varieties. A variety is classified to a specific maturity groups according to the length of period from planting to maturity. This phenological attribute is determined by two abiotic factors: photoperiod and temperature (Mourtzinis and Conley, 2017), and these factors can dictate the most suitable maturity groups of soybean varieties for a particular geographical location. Therefore, development of new varieties under different maturity class of soybean varieties for specific agro-ecologies of western Oromia and similar agro-ecologies is a priority option to boost soybean production and productivities in the region.

Varietal origin and evaluation

Gute soybean [*Glycine max* (L.) Merr.] variety designated by pedigree of PM 12-3 was brought from Jimma Agricultural Research Center. This variety was evaluated against twelve other pipeline genotypes and the standard check at Bako, Billo Boshe and Gute experimental sites from 2016/2017 to 2017/2018.

Agronomic and morphological characteristics

Gute is characterized by round in seed shape, gray seed coat color and creamy seed coat luster. It is indeterminate and

has erected growth habit, which enable harvesting at the same time and prevent from pod rot during heavy rain fall. Gute has large seed size compared to the commercial variety, PARC-3 (Table 1). Their leaf size is large and more uniform and is suitable for intercropping with erected leaf type maize varieties. The mean data from three locations (Bako, Billo-Boshe and Gute) and for two years (2016/2017 and 2017/2018) revealed that Gute flowered in 74 days and matured in 141 days. Gute has better seed size, hundred seed weight and pod load than the check PARC-3 (Table 1).

Yield performance

Gute soybean variety was evaluated with standard check PARC-3, in multi-locations yield trials. Gute gave a seed yield ranging from 1.8 to 2.7 ton ha⁻¹ on research stations and 1.5 to 2.4 ton ha⁻¹ on farmers' fields (Table 1). Gute outperformed PARC-3 by 20 % and 14 % yield advantage on station and on-farm in seed yield, respectively.

Oil and protein content

About 22.3 % of oil content was recorded from Gute while was 22.6 % recorded from the commercial variety PARC-3. The laboratory result revealed that Gute had higher protein content and comparable oil content with PARC-3. However, the newly released Gute soybean variety had higher protein content (39.4 %) than the commercial variety PARC-3.

Table 1: Agronomic/morphological characteristics of Gute variety

Characteristics	Gute (PM-12-3)
Adaptation area	
Altitude m (a.s.l)	1650-1900
Rainfall (mm)	1000-1200
Fertilizer rate (NPS) kg ha ⁻²	100
Fertilizer application time	At sowing
Fertilizer application method	Side dressing & avoid seed contact
Planting and seeding	
Planting date	Mid-June
Seeding rate (kg ha ⁻¹)	60-70
Row spacing (cm)	60
Plant spacing (cm)	10
Weeding frequency	3-4
Days to flowering	74
Days to maturity	141
Number of pods plant ⁻¹	81
Number of seeds pod ⁻¹	3
Leaf size	Large
Growth habit	Indeterminate
Seed coat color	Light yellow
Seed coat luster	Dull
Helium color	White
Seed shape	Round
Seed size	Medium
100 seeds weight	20
Oil content (%)	24.35
Protein content	39.4
Crop pest reaction (1-9 scale)	
Bacterial blight	2.75
Bacterial pustule	2.75
Rust	2.5
Yield (ton ha ⁻¹)	
Research field	1.8-2.7
Farmer field	1.5-2.4
Year of release	2020

Stability and Adaptability Performance

Genotype x environments interaction was partitioned into principal component axes and the first IPCA (69.28%) and the second IPCA (22.41%) explained the largest proportion (91.68 %) of the total

variation. The result of the study revealed that Gute (PM-12-3) is ideal and stable varieties compared to the commercial variety, PARC-3 (Figure 1). Gute was found to be a more stable new soybean variety and higher in oil content compared to the commercial variety PARC-3.

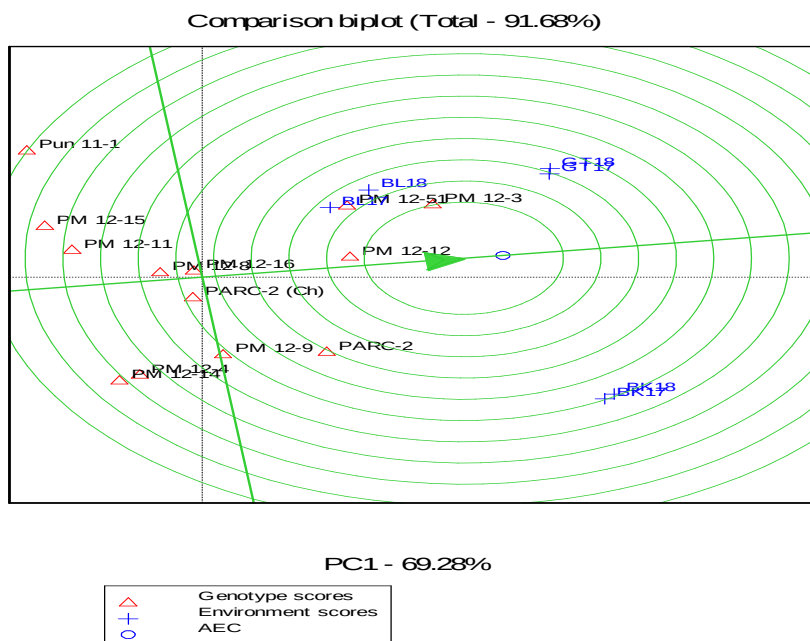


Figure 1: Ranking the genotypes relative to the ideal genotype.

Reaction to Major Diseases

The major soybean diseases in western Oromia such as bacterial blight, bacterial pustule and rust were recorded using 1-9 scale. Accordingly, Gute (PM-12-3) was resistant (< 3 severity score for the three major diseases recorded (Table 1).

Breeder Seed Maintenance

Breeder and foundation seed of the variety is maintained by Oromia Agricultural Research Institute Bako Agricultural Research Center.

Conclusion

The soybean variety Gute had higher seed yields, protein content,

comparable oil content and better stability performances than the commercial variety PARC-3. The variety was also resistant to common soybean diseases viz., bacterial blight, rust and bacterial pustule and hence, have been released for the test environments and areas with similar agro-ecologies.

Acknowledgement

We gratefully thank Agricultural Growth Program (AGP-II) of Oromia Agricultural Research Institute for financing the development of the variety. We also thank International Institute of Tropical Agriculture (IITA) and Jimma Agricultural Research Center for germplasm sharing. Our appreciation and thank extended to staff members of Bako

Agricultural Research Center for field work and data collection.

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Ethiopian Journal of Crop Science (EJCS)

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Ethiopian Journal of Crop Science

P.O. Box 2003, Addis Ababa

Ethiopia

Ethiopian Journal of Crop Science

Volume 8

Number 2

January 2020

ISSN 2072-8506

Assessment of the Potential Impacts of Climate Change in Agricultural Catchment: The Case of Fincha, North western Ethiopia

Wakjira Takala Dibaba, Tamene Adugna Demissie and Konrad Miegel 1

Artificial Intelligence Assisted Early Blight and Late Blight Potato Disease Detection

Using Convolutional Neural Networks
Natnael Tilahun and Beakal Gizachew 15

Genetic Variability and quantitative traits inheritance in Sesame (Sesamum indicum L.) Genotypes

Feyera Takele, Dagnachew Lule and Sentayehu Alemereu 29

Trends in Observed Temperature and Rainfall Variability in Major Potato Growing Districts of Eastern Ethiopia

Simeret Burga, Kindie Tesfaye, Nigussie Dechassa, Tamado Tana and Wassu Mohammed 43

Yield Stability Analysis of Soybean Varieties (early set) in Western Oromia, Ethiopia

Adane Arega, Alemayehu Dabessa and Solomon Bekele 67

Genotype by Environment Interaction and Grain Yield Stability of Striga Resistant Sorghum [Sorghum bicolor (L.) Moench] Genotypes in Ethiopia

Fantaye Belay, Firew Mekbib and Taye Tadesse 79

The Release and Registration of Bako-09 (Acc. 214995) Finger millet Variety

Kebede Dessalegn, Dagnachew Lule, Kassa Mamo, Girma Mengistu, Girma Chemed, Megersa Debela, Megersa Kebede, Chemed Birhanu, Hailu Feyisa, Geleta Gerema, Fufa Anbessa and Gudeta Bedada 101

The Release and Registration of Gute (Late Set) Soybean Varieties

Adane Arega and Alemayeh Dabessa 107

Guidelines for Contributors 113

Price: 50 Birr