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Model-based yield gap analysis and constraints of rainfed sorghum production in Southwest Ethiopia

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Abstract

For ensuring food demand of the fast growing population in developing countries, quantification of crop yield gaps and exploring production constraints are very crucial. Sorghum is one of the most important climate change resilient crops in the rainfed farming systems of semi-arid tropics. However, there is little information about yield gaps and production constraints. This study aimed at analysing existing yield gaps and exploring major constraints of sorghum production in Southwest Ethiopia. A crop simulation model approach using AquaCrop and DSSAT was used to estimate potential yield and analyse the yield gaps. Model calibration and evaluation was performed using data from field experiments conducted in 2018 and 2019. Sorghum production constraints were assessed using a survey. The actual and water-limited yield of sorghum ranged from 0.58 to 2.51 and 3.6 to 6.47 t/ha, respectively for the period 2003–17. The regional yield gaps of sorghum for the targeted period were 3.02–3.95 t/ha with a mean value of 3.51 t/ha. Majority of respondent farmers considered seasonal rainfall risk (98%), poor soil fertility (86%), lack of improved varieties (78%) and inadequate weed management (56%) as major factors responsible for the existing yield gaps. The mean exploitable yield gap (2.5 t/ha) between water-limited and actual yield showed the level of existing opportunity for improvement in the actual productivity of sorghum. The gaps also call for introduction of proper interventions such as adoption of improved varieties, planting date adjustment, conservation tillage, fertilizer application and on time weed management.

Introduction

The rapid population growth accompanied by natural resource degradation, dependence on rainfed agriculture and impact of climate change has constrained food security of developing countries such as Ethiopia (Endalew *et al.*, 2015; Reynolds *et al.*, 2015; Mekuria, 2018). Increased agricultural production in developing countries mainly comes from area expansion and little from technological interventions (Tilman *et al.*, 2011; Van Loon *et al.*, 2019). Small shares of land by farmers due to population pressure and also its degradation limit production and productivity of crops in Ethiopia, which altogether call for designing strategies to maximize productivity per unit of existing cultivated land (Gebreselassie, 2006; Najafi *et al.*, 2018). Additionally, food production capacity of farm land, change in crop yield and the existing yield gaps need to be evaluated in a holistic approach to provide information for policy makers and farmers to optimize the management system of their farm lands and increase food production by reducing further area expansion (van Wart *et al.*, 2013a; Anderson *et al.*, 2016; Najafi *et al.*, 2018).

Quantification of crop yield gaps (Y_g) provides key information as a basis for identifying production constraints, exploring ways to increase crop productivity and prioritization of intervention areas (Chapagain and Good, 2015; FAO, 2017; Eash *et al.*, 2019). Moreover, exploring existing yield gaps together with production constraints is the key for accurate assessment of future food security, land use change and productivity (Van Ittersum *et al.*, 2013). In this regard, a number of findings having global, regional and local emphasis have been reported and generated important information using different methodologies for the last few decades (Lobell *et al.*, 2009; Van Wart *et al.*, 2013b; Anderson *et al.*, 2016; Beza *et al.*, 2017; Soltani *et al.*, 2020).

Benchmarking of potential yield (Y_p) from maximum farmer yield, field experiments and crop model simulations are the three common methods to estimate potential yield of crops for employing Y_g analysis (Laborte *et al.*, 2012; FAO and DWFI, 2015). There are different limitations when Y_p is taken from maximum farmer yield and field experiments (Lobell *et al.*, 2009). For instance, for the estimation of Y_p from field experiments perfect growth conditions have to

be implemented throughout the growing season over a number of years to reflect the effect of climatic variation, which is quite difficult to realize. Similarly, maximum farmers' yield is based on the report of individual farmers, which may be prone to data quality problems. On the contrary, crop simulation models have quite significant importance because models account for the variability of multiple years' weather conditions and allow interactions among crops, soil, weather, water regime and management to come up with a better estimate of Y_p (Van Ittersum *et al.*, 2013). Thus crop models provide the most accurate ceiling of Y_p for a particular location despite having uncertainties related to parameter estimation or structural functioning (Lobell *et al.*, 2009; Soltani and Sinclair, 2012; Eitzinger *et al.*, 2013).

Sorghum (*Sorghum bicolor* (L.) Moench) is the fifth most important cereal crop next to maize, rice, wheat and barley globally (FAOSTAT, 2017). It is grown in semi-arid tropics including Ethiopia where other crops perform poorly, making it an important climate change resilient and food security crop (Amelework *et al.*, 2016; Hadebe *et al.*, 2017a; Smale *et al.*, 2018; Eggen *et al.*, 2019). Sorghum is the third widely cultivated cereal crop next to Teff and maize and took third rank on its productivity next to maize and wheat in Ethiopia (CSA, 2016, 2017). South Omo and Segen Area People's Zones are its production belts in Southwest Ethiopia (CSA, 2016, 2017). Most parts of this region are located in hot arid and semi-arid agro-ecological zones with recurrent droughts, which exerts a negative impact on food security of the population (Gebremichael *et al.*, 2014; Enyew and Hutjjs, 2015). Hence, it is essential to deal with the existing production status of crops such as sorghum, which have better adaptation capacity to such environments (Hadebe *et al.*, 2017a).

Bottom-up approaches, up scaling site-specific Y_p and Y_g estimates to regional and national scales according to Global Yield Gap Atlas (www.yieldgap.org) is praiseworthy methodology for the estimation of regional and national Y_p and Y_g of crops (van Wart *et al.*, 2013b; van Bussel *et al.*, 2015). Robust, calibrated and evaluated models for Y_p and Y_g estimates based on in-season time series of crop and soil states and weather data have paramount importance for generating valid information (Rötter *et al.*, 2012; Kassie *et al.*, 2014; Pradhan *et al.*, 2015). In this regard, estimates of sorghum water-limited yield (Y_w) ranging from 0.9 to 11.1 t/ha and Y_g of 4.9 t/ha were done in Ethiopia using a crop model (WOFOST) to generate data for the Global Yield Gap Atlas (Van Bussel *et al.*, 2015; www.yieldgap.org). In this study, calibration of the model and simulation of Y_w of sorghum were done using soil data generated from ISRIC World Soil information having 30–70% uncertainty that limits the accuracy of model simulation (<https://www.isric.org/explore/soilgrids/faq-soilgrids>). Furthermore, crop and management data were taken from previous studies and expert judgement, which altogether raise question on input data quality and reduce accuracy of model simulation by introducing additional uncertainty (Bao *et al.*, 2017). In the current study, observed crop and soil data for model calibration and evaluation were taken from field experiment conducted for this purpose in Southwest Ethiopia. Furthermore, the Y_w and existing Y_g of sorghum in the region were addressed using two crop models (AquaCrop and DSSAT) that use different crop coefficients and simulate crop yield based on different input data requirement (Raes *et al.*, 2018; Hoogenboom *et al.*, 2019a). In addition, the current yield gap analysis was linked to identification of the factors responsible for the existing yield gap in order to indicate possible areas of intervention. Hence, this study was carried out with objectives

of analysing existing yield gaps and exploring major production constraints of rainfed sorghum production in Southwest Ethiopia.

Materials and methods

Description of study area

The study was conducted in two administrative zones (South Omo and Segen Area People's zones) of Southwest Ethiopia (Fig. 1), which are known for sorghum production in acreage and productivity in the region (CSA, 2016). From the cultivated land in the region, sorghum area coverage ranked second (20%) next to maize (CSA, 2020). South Omo zone has an altitude ranging from 376 to 3500 m a.s.l. and located between 35°97'–36°6'E and 4°43'–6°46'N (BoFED, 2012). Similarly, Segen Area People's zone has an altitude ranging from 501 to 3000 m a.s.l. and located between 37°1'–38°01'E and 5°17'–5°59'N. The region has a mean annual rainfall of 435–1211 mm while annual maximum and minimum temperature ranges from 27.8 to 33.7 and 14.4 to 23.7°C, respectively.

Description of the field experiment

A field experiment was conducted during the main cropping season (February to June) for 2 years (2018 and 2019) to collect crop and soil data for model calibration and evaluation. The experiments were run at two locations, Jinka Agricultural Research Centre having an altitude of 1380 m a.s.l. (hereafter called Jinka) and Kako Farmers Training Centre having elevation of 1196 m a.s.l. found in Benatsemay district (hereafter called Benatsemay), in South Omo zone, Southwest Ethiopia (Fig. 1). Benatsemay and Jinka were selected to represent low land and areas near-mid land conditions where sorghum is commonly produced in the region, respectively. The study involved two improved sorghum cultivars (Melkam and Teshale) that were introduced to the area by Ethiopian Institute of Agricultural research. Both cultivars are adopted by farmers in the region although still many used their local cultivars. Teshale is relatively high yielder, more susceptible to bird attack and have short storage life compared to Melkam. On the contrary, Melkam has short plant height and mature relatively earlier than Teshale (Jinka, unpublished). Four rates (0, 50, 100 and 150 kg/ha) of the blended fertilizer consisting of nitrogen, phosphorus, sulphur and boron (NPSB) based on the recommendation by EhtioSIS soil Fertility Map (EthioSIS 2016, unpublished) were considered as the second factor for the field experiment. Higher rates of nutrients were included to determine the best genetic coefficients of the sorghum cultivars used. The treatments were combined in factorial arrangement and laid out in randomized complete block design with three replications.

Models and data requirement

AquaCrop and DSSAT models

A model-based approach was selected for this study from the different methods available for yield gap analysis. Two crop models, CERES-Sorghum model that is embedded in the Decision Support System for Agrotechnology Transfer (DSSAT v. 4.7.5 – a complex model (Jones *et al.*, 2003; Hoogenboom *et al.*, 2019a, 2019b)) and AquaCrop (Version 6.1, an intermediate model (Steduto *et al.*, 2009; Raes *et al.*, 2018)) were employed. The two models were selected based on their wide applicability and

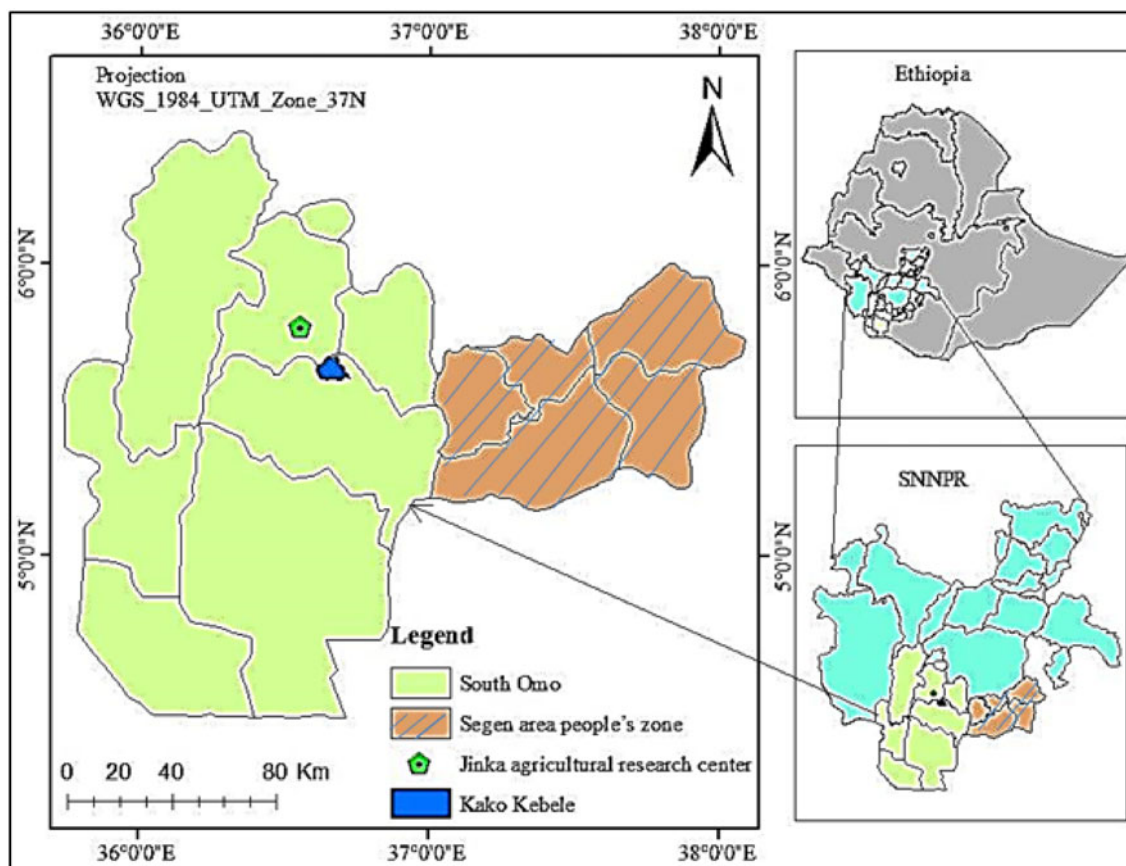


Fig. 1. Map of study area. SNNPR, Southern Nations Nationalities and Peoples' Regional State.

acceptance for the estimation of potential yield, adaptation option evaluation, impact assessment of climate change and optimization of field managements (Tsegay *et al.*, 2012, 2015; Kassie *et al.*, 2014; Lopez *et al.*, 2017; Adam *et al.*, 2018).

Differences in input data requirement and simulation processes were the other reasons for selecting the two models, as indicated below. Furthermore, the interest in using the two models was to compare their performance in predicating Y_w of sorghum cultivars without considering the essence of a multimodel approach. AquaCrop, developed by the FAO, is a user-friendly and practitioner-oriented model, which maintains an optimal balance between accuracy, robustness and simplicity (Steduto *et al.*, 2009; Raes *et al.*, 2018). It uses only a relatively small number of explicit parameters and mostly intuitive input variables that can be determined by using simple methods, while the calculation procedures are based on basic and often complex biophysical processes to guarantee an accurate simulation of the crop response in the plant–soil system (Raes *et al.*, 2009; Steduto *et al.*, 2009). It simulates biomass and yield production based on the amount of water transpired from green canopy cover under the governing environmental conditions. Aboveground biomass (B) is produced as a function of the daily ratio of crop transpiration Tr_i (mm) and reference evapotranspiration (ET_o) via crop water productivity WP^* (g/m^2) that is normalized for ET_{o_i} (mm) and atmospheric CO_2 concentration (Steduto *et al.*, 2009; Raes *et al.*, 2018):

$$B = WP^* \cdot \sum_{i=1}^n \left(\frac{Tr_i}{ET_{o_i}} \right)$$

where n is the sequential days spanning the period when B is produced.

DSSAT is the most widely used crop model globally, which consists of a collection of independent programmes (crop, weather, soil and water modules) that operate together, with the cropping system model embedded in its heart (Jones *et al.*, 2003). DSSAT simulates growth and development of a crop grown under prescribed or simulated management, soil water, carbon and nitrogen. Phenological development and growth of a crop are specified in DSSAT by cultivar-specific genetic coefficients (Hoogenboom *et al.*, 2019a).

Input data sets and observed data for model calibration

AquaCrop uses inputs from climate, crop, soil and management files (Hsiao *et al.*, 2009). The climate data include daily values of minimum and maximum air temperature, rainfall, reference evapotranspiration (ET_o), which can be computed from wind speed, relative humidity, sunshine hours and minimum and maximum air temperatures (Raes *et al.*, 2018). Climate data measured by the National Metrology Agency of Ethiopia (NMA) from 2003 to 2019 at two weather stations (Jinka and Keyafer) located near the experimental sites were collected and quality control was checked using the Rclimdex software program (Zhang and Yang, 2004).

The crop data for AquaCrop include, time of emergence, maximum canopy cover, days to flowering, senescence and maturity that were used to simulate dry aboveground biomass and grain yield. Seasonal canopy cover, dry aboveground biomass and soil

water content were the data collected to be used for model calibration and evaluation. Canopy cover was determined using 'sample-point' software by taking digital pictures perpendicular to the experimental plot at a height of 2 m (Booth *et al.*, 2006). Phenology data were collected by field observation when 50% of plants in each experimental unit reached the respective stages. Green canopy cover and aboveground biomass were measured at 10-day interval starting from emergence to maturity. Similarly, the soil inputs included texture, number of horizons in the root zone, initial soil water content, field capacity (FC), permanent wilting point (PWP) and soil nutrient content. The initial soil conditions of experimental sites (Table 1) were determined after excavating a soil profile at each site during planting at a depth of 1.2 m. Apart from the nutrient analysis (used during simulation of DSSAT and not shown here), soil texture, total available water and bulk density were determined at soil laboratories of Hawassa University and Jinka. The soil water retention at PWP, FC and saturation (SAT) were determined using a pedo-transfer function based on the textural class of the soil (Saxton and Rawls, 2006). Seasonal available soil water content was measured using a gravimetric method at 10-day interval starting from sowing to crop maturity. Additional information on soil texture, organic matter content, electric conductivity, pH and exchangeable potassium was used from the data generated by Kebede *et al.* (2017) for different soil conditions of Jinka.

The DSSAT model uses soil, crop management and daily meteorological data as input to simulate daily leaf area index (LAI) and vegetation status parameters, biomass production and final yield (Jones *et al.*, 2003; Hoogenboom *et al.*, 2019a). The daily meteorological data include solar radiation, rainfall and maximum and minimum air temperatures. The main soil data include soil type, slope and drainage characteristics, and physico-chemical parameters for each soil layer. The crop management data include variety, planting date, plant density and fertilizer application. The entire crop, soil and management data were taken from the field experiment. Solar radiation was estimated from the available sunshine hours using the Angstrom formula (Allen *et al.*, 1998):

$$R_s = (0.25 + 0.5 \left(\frac{n}{N}\right)) R_a$$

where R_s is the solar radiation ($\text{MJ}/\text{m}^2/\text{day}$), R_a is the extra-terrestrial radiation ($\text{MJ}/\text{m}^2/\text{day}$), n is the actual duration of sunshine (h) and N is the maximum possible sunshine duration (h).

Model calibration and evaluation

Model calibration is an adjustment of system parameters for gaining a good overall agreement between simulated and observed values, so that simulation output would fairly fit the reality (Sannagoudar *et al.*, 2019). Calibration of both AquaCrop and DSSAT models was done using relevant data (phenology, canopy cover, soil water content, LAI, biomass and yield) from the field experiment conducted in 2018 for the two improved sorghum cultivars (Melkam and Teshale) recommended for the area.

Four coefficients (canopy growth, maximum canopy cover, average canopy decline and water productivity) were manually adjusted until the simulated seasonal green canopy cover, aboveground biomass and soil water content approximated to the observed values during the calibration of AquaCrop. Similarly, during calibration of DSSAT, genetic coefficients that influence

Table 1. Soil properties at Benatsemay and Jinka experimental sites, Southwest Ethiopia

Soil depth (cm)	Benatsemay			
	0–20	20–40	40–80	80–120
Texture	Sandy loam	Sandy loam	Loamy sand	Sandy loam
BD (g/cm^3)	1.52	1.38	1.42	1.39
SAT (vol%)	43.8	43.2	44.1	43.0
FC (vol%)	16.5	19.9	14.0	21.2
PWP (vol%)	9.7	12.1	8.5	13.2
TAW (mm)	98	84	85	80
Jinka				
Texture	Clay loam	Clay loam	Clay	Clay
BD (g/cm^3)	1.35	1.36	1.32	1.3
SAT (vol%)	48.9	48.6	50.2	50.8
FC (vol%)	37.9	36.8	40.3	41.8
PWP (vol%)	23.9	22.3	27.0	29.1
TAW (mm)	145	140	130	130

BD, bulk density; SAT, soil water retention at saturation; FC, soil water retention at field capacity; PWP, soil water retention at permanent wilting point; TAW, total available water in the root zone of 1.2 m.

phenology, growth and yield were developed by employing a GLUE coefficient estimator (Jones *et al.*, 2011) using data from the field experiment of 2018. Cultivar parameters that influence biomass accumulation and grain yield were determined after adjusting the coefficient for phenology (anthesis and maturity dates).

Performance evaluation of the two models was done to test if the output of model simulations reaches an adequate level of agreement with the observed values (Tsegay *et al.*, 2012). Evaluation of AquaCrop performance was done using independent data sets from field experiment of 2019 involving green canopy cover, soil water content and aboveground biomass without making any changes on the calibrated crop file. Similarly, DSSAT was evaluated using point data from a specific period such as days to anthesis and physiological maturity and time series data of biomass, LAI and soil water content collected from the same field experiment.

Statistical indicators that were used to compare the deviation between observed and simulated values were root mean squared error (RMSE) (Chai and Draxler, 2014) and index of agreement (d) (Willmott, 1982). The RMSE is a measure of the mean deviation between observed and simulated values that indicate the absolute model uncertainty. It has the same unit as the variable being simulated, and a value closer to zero indicates better model simulation performance:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (O_i - S_i)^2}$$

where O_i and S_i are the observed (measured) and simulated values, respectively and N is the number of observations. The

index of agreement is a measure of relative error in model estimates that ranges from 0 to 1.0, where 0 and 1 describe complete disagreement and agreement between estimated and observed values, respectively:

$$d = 1 - \frac{\sum_{i=1}^N (S_i - O_i)^2}{\sum_{i=1}^N (|S_i - \bar{O}| + |O_i - \bar{O}|)^2}$$

where \bar{O} is the mean of observed (measured) values. Additionally percent bias (PBIAS) was used to measure the tendency of simulated data to be smaller or larger than the observed data (Moriasi *et al.*, 2007):

$$\text{PBIAS} = \frac{\sum_{i=1}^N 100 (O_i - S_i)}{\sum_{i=1}^N (O_i)}$$

Positive values indicate underestimation, negative values indicate overestimation and zero value indicates agreement of averages of simulated and measured values.

Approaches for yield gap and variability analysis

Water-limited yield and yield gaps existing in the region were estimated with the two models using multi-year simulations based on historical weather data. Yield gap analysis can be done by comparing two levels of yield from different yield categories (Lobell *et al.*, 2009; Kassie *et al.*, 2014; FAO and DWFI, 2015) involving potential yield, water-limited yield, attainable yield and average farmers yield (actual yield). Potential yield is the maximum yield of a crop cultivar grown in an environment to which it is adapted with nutrients and water non-limiting and pests, diseases, weeds, lodging and other stresses effectively controlled. Water-limited yield (Y_w) is similar to potential yield, except that yield is limited by water supply, and hence influenced by soil type (water holding capacity and rooting depth) and field topography. The former and later are used as the benchmark of productivity to irrigated and rainfed crops, respectively.

Attainable yield is the best yield achieved through skilful use of the available technologies by avoiding the effect of weeds, pests and diseases while water and nutrients limit the yield. Similarly, average farmers yield (Y_a) is the yield achieved using the available resources and current practices of the farmers and determined from an area and production data of a crop for a given district and time period. In addition, on farm trial yield data were taken from experiments conducted at Farmers Training Centre of three districts in South Omo (Benatsemay, Nangaton and Dasenech) by researchers from Jinka. The trial was conducted to evaluate adaptation of improved sorghum cultivars using recommended technologies such as spacing (75 by 15 cm²), fertilization (100 kg/ha urea), weed control (three times weeding) and planting date (varied from February to March). Water-limited yield, attainable yield and actual yield were represented with data generated from crop simulation models, farm trials and average farmers' yield (from Central Statistical Agency (CSA)), respectively. Due to rainfed nature of sorghum production in the country including the study area, Y_w was used instead of Y_p during yield gap analysis. Accordingly, the following three types of Y_g analyses were done: (i) the gap between water-limited and attainable yield, (ii) the gap between water-limited and actual yield and (iii) the gap between attainable and actual yield. Comparison of actual yield from CSA, average yield value at the

zone level, with water-limited yield of sorghum from two sites within the zone was the limitation of this study. Hence there was a possibility of over or under estimation of the yield gap to some extent.

Sorghum production constraints

In addition to the field experiment, a survey was conducted in 2019 to identify sorghum production constraints in South Omo and Segen Area People's zones. For this study, four *kebeles* (the lowest administrative unit in Ethiopia) were selected using multi-stage sampling techniques. First, South Omo and Segen Area People's zones were selected purposefully owing to their potential of sorghum production in the southern region. Similarly, Benatsemay district from South Omo zone and Konso district from Segen Area People's zone were selected based on the same criteria and two *kebeles* from each district were picked randomly. Based on the following sample size determination formula (Yamane, 1967), the total sample size of the four identified *kebeles* was 354:

$$n = \frac{N}{1 + N e^2}$$

where n is the sample size and N is the population size (3055) and e is the desired level of precision (0.05). However, due to the scattered settlement of the population and harsh environmental conditions, the total sample size was reduced to 245. By using the list of household heads from each district agricultural office, 245 farm household heads from the four *kebeles* were sampled randomly using probability proportional to the size of the total households of each *kebele*. A semi-structured questionnaire was used to gather information on farm history, agronomic practices used by farmers and challenges they faced in relation to reduced productivity of sorghum in the area. Descriptive data analysis was done to summarize responses from the farmers on the factors reducing sorghum yield.

Results

Model calibration and evaluation

The crop parameters adjusted for cultivars Melkam and Teshale during the calibration of AquaCrop were maximum canopy cover, canopy growth coefficient, normalized water productivity and average canopy cover decline. These parameters influence the expansion of green canopy cover, biomass accumulation and yield formation of a given crop. The adjusted values of Teshale and Melkam were 48.6 and 56.4% for maximum canopy cover, 8.29 and 10.26% for canopy growth coefficient, 0.84 and 0.94%/day for average canopy decline and 9.6 and 9.3 g/m² for normalized water productivity, respectively (Table 2). After calibration, the RMSE values were 6.2 and 6.3% for canopy cover, 0.65 and 0.68 t/ha for dry aboveground biomass of Melkam and Teshale, respectively (Table 3). In addition, the RMSE for soil water content was 8.7 mm (Table 3). Similarly, the values of d and PBIAS ranged from 0.95 to 0.97 and -9.18 to -3.2%, respectively.

The evaluation of AquaCrop using independent observation data of seasonal green canopy cover, aboveground biomass and soil water content from 2019 (Figs 2 and 3) confirmed a good agreement between simulations and observations during the

calibration year 2018 (Table 3). Simulation of available soil water content in the root zone showed a deviation of 2.2 mm (Table 4). The average observed canopy covers of 33.4% for Melkam and 30.7% for Teshale were simulated by the model with deviation of 0.9 and 2.4%, respectively (Table 4). Similarly, simulation of aboveground biomass showed a deviation of 0.11 t/ha for Melkam and 0.1 t/ha for Teshale.

The d values were >0.9 for all cases of green canopy cover and dry aboveground biomass except for seasonal soil water content for which d was 0.83 (Figs 2 and 3) during the evaluation of AquaCrop. Similarly, the RMSE were 6.9 and 5.8% for green canopy cover and 0.55 and 0.96 t/ha for dry aboveground biomass of Teshale and Melkam, respectively. In addition, the RMSE for soil water content was 7.6 mm. Furthermore, the slopes of correlation lines between observed and simulated seasonal soil water content and crop parameters were almost parallel and approached to 1:1 plot and the statistical measures were adequate to show the accuracy of the model to simulate soil water content, green canopy cover and dry aboveground biomass (Figs 2 and 3).

Table 5 shows the cultivar coefficients adjusted during DSSAT calibration for simulating development and growth of sorghum cultivars. Evaluation of DSSAT using these calibrated cultivar coefficients showed a good agreement between observed and simulated phenology and growth of sorghum cultivars (Table 6). The observed days to anthesis and maturity were 71 and 106 for Melkam and 76 and 114 for Teshale, respectively. Deviations of simulated value for days to anthesis and maturity were 2 and 6 for Melkam and 1 and 3 for Teshale, respectively. Similarly, maximum LAI was simulated with a deviation of 0.17 for Melkam and 0.54 for Teshale. The simulated seasonal top weight, LAI and water available in the root zone showed a good fit with the observed values and the regression lines between simulated and observed values were almost parallel and approached to 1:1 plot (Figs 4 and 5).

A grain yield of 4.2 t/ha for the cultivar Melkam and 4.7 t/ha for Teshale were obtained from the field experiment of 2019 (Table 7). During model evaluation, grain yields of 5.1 and 5.6 t/ha were achieved from the simulation of AquaCrop for cultivar Melkam and Teshale, respectively (Table 7). Similarly, simulation by DSSAT resulted in a grain yield of 4.6 t/ha for Melkam and 4.9 t/ha for Teshale, which were lower than the values obtained from AquaCrop. There was a good agreement between observed and simulated values of grain yield for both models (Table 7). However, grain yield was simulated with lower deviation using DSSAT (average deviation of 0.3 t/ha) than AquaCrop (average deviation of 0.9 t/ha) compared to the average measured yield of the two cultivars over locations. Also simulated grain yield of both cultivars had lower PBIAS for DSSAT than AquaCrop (Table 7). The maximum PBIAS (−21.4%) was observed for grain yield of Melkam simulated with AquaCrop and the minimum PBIAS (4.3%) was observed for Teshale simulated with DSSAT.

Yield levels, variability and gaps

The regional actual yield of sorghum for the period 2003–17 varied from 0.58 to 2.51 t/ha with an average of 1.51 t/ha and coefficient of variation (CV) of 40.3% (Table 8, Fig. 7). Similarly, the mean attainable yield of sorghum for the period 2014–17 was 3.06 t/ha with a CV of 30.8% (Table 8). The Y_w of Melkam as simulated with AquaCrop ranged from 4.55 to 5.78 t/ha with an average of 5.14 t/ha at Jinka and from 3.51 to 6.28 t/ha at Benatsemay with a mean value of 5.01 t/ha (Fig. 6). The values

Table 2. Adjusted crop coefficients during calibration of AquaCrop for sorghum cultivars in Southwest Ethiopia

Coefficient	Cultivar	
	Teshale	Melkam
Maximum canopy cover (%)	48.6	56.4
Canopy growth coefficient (%)	8.29	10.26
Average canopy decline (%/day)	0.84	0.94
Water productivity (g/m ²)	9.6	9.3

Table 3. Statistical measures for soil moisture and crop growth after calibration of AquaCrop in 2018

Parameter	Cultivar	RMSE	d	PBIAS (%)
Soil moisture (mm)		8.7	0.95	−8.43
Canopy cover (%)	Melkam	6.2	0.95	−8.43
Dry aboveground biomass (t/ha)		0.65	0.96	−3.2
Canopy cover (%)	Teshale	6.3	0.96	−9.18
Dry aboveground biomass (t/ha)		0.68	0.97	−8.95

RMSE, root mean squared error; d , index of agreement; PBIAS, percent bias.

with DSSAT were 3.1–6.5 t/ha with a mean of 4.69 t/ha at Jinka and 3.13–7.44 t/ha with a mean of 5.12 t/ha at Benatsemay (Fig. 6). Cultivar Teshale had Y_w of 5.15–6.24 t/ha with a mean of 5.49 t/ha and 3.81–6.53 t/ha with a mean of 4.92 t/ha as simulated with AquaCrop and DSSAT, respectively, at Jinka. The Y_w of this cultivar ranged from 4.03 to 5.91 t/ha with an average of 5.24 t/ha for AquaCrop and from 3.12 to 7.08 t/ha with an average of 4.83 t/ha for DSSAT at Benatsemay (Fig. 6). Inter-annual variability was also observed from the time series analysis of Y_w (Table 8, Fig. 7). Coefficients of variation for Y_w averaged for the two cultivars were 4.5% at Jinka and 12.2% at Benatsemay for AquaCrop. Similarly, CV for Y_w averaged for two cultivars were 19.3 and 22.3% at Jinka and Benatsemay, respectively, with DSSAT.

The 90th percentile of Melkam Y_w was 5.75 t/ha at both Jinka and Benatsemay using AquaCrop and 6.01 t/ha at Benatsemay and 5.74 t/ha at Jinka using DSSAT (Fig. 6). Similarly, for the cultivar Teshale the values were 5.85 t/ha at Benatsemay and 5.24 t/ha at Jinka using AquaCrop, and 5.72 t/ha at Benatsemay and 5.42 t/ha at Jinka using DSSAT (Fig. 6). Also, higher medians of Y_w were recorded for both cultivars at Benatsemay than Jinka with the two crop models except for Melkam using AquaCrop at Jinka (Fig. 6).

The regional yield gaps between actual yield and Y_w (mean of the two cultivars) simulated using AquaCrop and DSSAT ranged from 2.39 to 4.69 t/ha and 1.15 to 5.51 t/ha, respectively (Fig. 7). The average Y_g between actual yield and Y_w , averaged for the two cultivars were 3.62 and 3.44 t/ha at Benatsemay and 3.81 and 3.23 t/ha at Jinka simulated with AquaCrop and DSSAT models, respectively, with an average value of 3.53 t/ha (Table 9). The differences between Y_w and attainable yield of sorghum ranged from 1.75 to 2.26 t/ha simulated with AquaCrop and DSSAT (Table 9). Additionally, the regional gap between attainable and actual yield was 1.55 t/ha (Table 9).

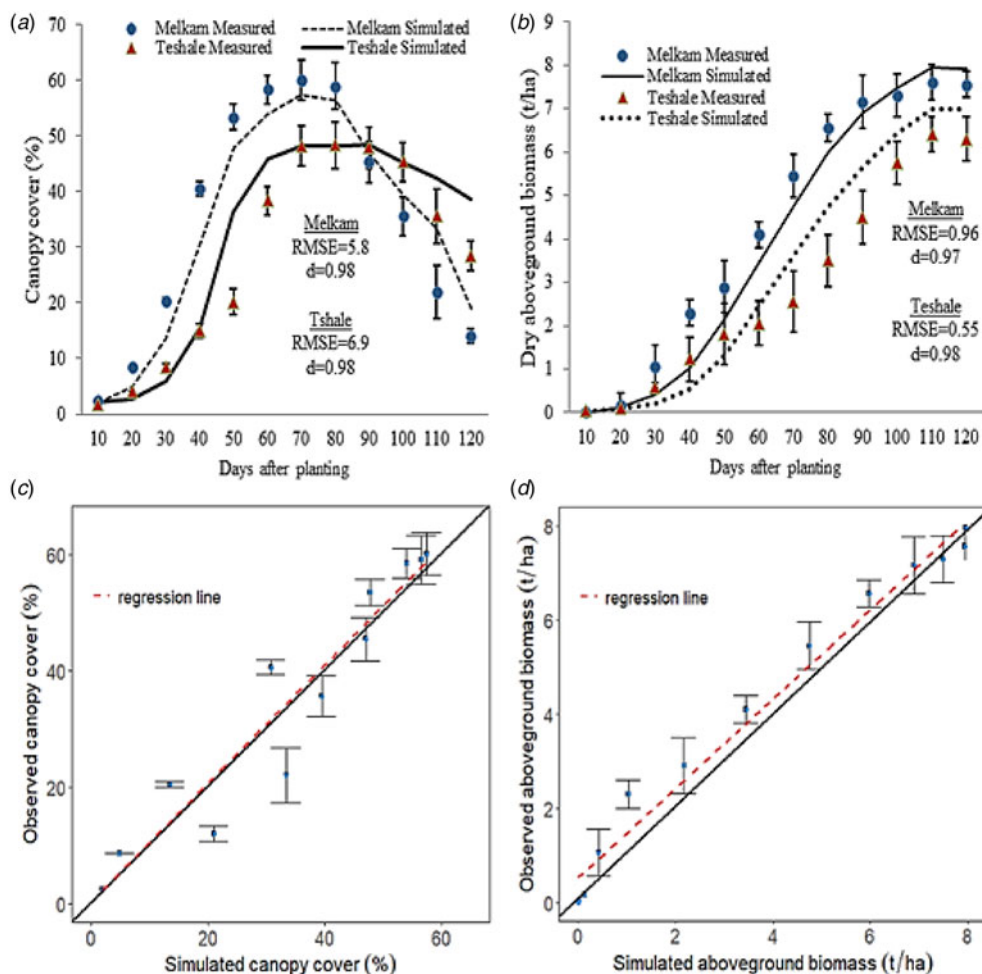


Fig. 2. Observed and simulated (AquaCrop) canopy cover (a) and aboveground biomass (b) of cvs. Melkam and Teshale, as well as regression between observed and simulated canopy cover (c) and aboveground biomass (d) of cv. Melkam during evaluation of AquaCrop at Jinka. The vertical bars indicate \pm standard deviation ($n = 3$).

Production constraints of sorghum

The existing yield gaps in Southwest Ethiopia were attributed to different factors as indicated by the survey (Fig. 8). Majority of respondent farmers (98%) considered seasonal rainfall risks as the first major factor for low productivity of sorghum. The survey result was in agreement with the correlation analysis of actual and water-limited yield of sorghum with growing season rainfall variability and patters (Figs 9 and 10). The regional growing season rainfall (averaged for eight weather stations of the region) and the actual regional yield had a correlation coefficient of 0.63 for the period 2003–17. Similarly, the correlation coefficient between growing season rainfall and water-limited yield of Melkam and Teshale simulated with AquaCrop and DSSAT at Benatsemay and Jinka ranged from 0.52 to 0.74. Furthermore, the water-limited yield generally increased with increasing of rainfall and vice versa. Similarly, farmers identified poor soil fertility (86%) as the second factor that limit sorghum productivity in the region. In agreement with farmers’ assessment, field experiment result confirmed that grain yield of sorghum cultivars increased by 77.3 to 83.6% due to the application of 150 kg NPSB/ha as compared to unfertilized plants (Table 10). Additionally, farmers identified a lack of improved varieties (78%) and poor weed management (56%) as other major factors limiting potential yield

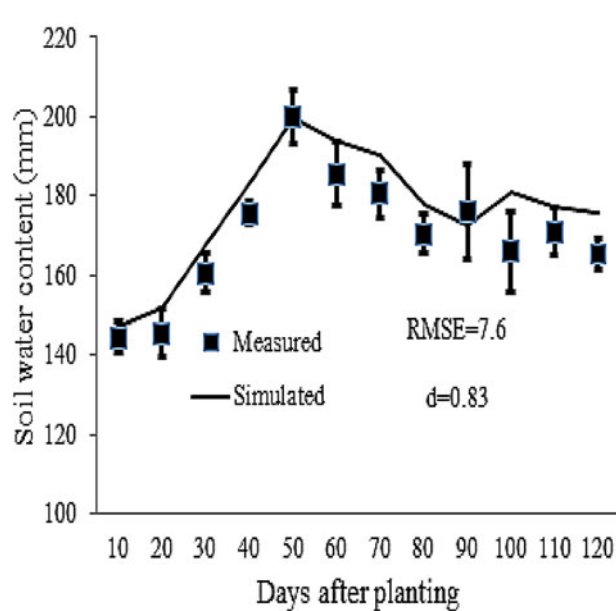


Fig. 3. Observed and simulated seasonal available soil water content in the root zone (1.2 m) during evaluation of AquaCrop at Jinka. The vertical bars indicate \pm standard deviation ($n = 3$).

Table 4. Comparison of observed and simulated average seasonal available soil water content, green canopy cover and aboveground biomass of sorghum cultivars in Southwest Ethiopia during evaluation of AquaCrop

Parameters	Melkam		Teshale	
	Observed	Simulated	Observed	Simulated
SWC (mm)	172.6	174.8	172.6	174.8
Canopy cover (%)	33.4	34.3	30.7	33.1
Dry aboveground biomass (t/ha)	3.52	3.63	3.22	3.32

SWC, available soil water content in the root zone. Unit of soil water content was changed from g/g to mm/m as per the requirement of AquaCrop.

Table 5. Calibrated genetic coefficients of sorghum cultivars used for evaluation of DSSAT model in Southwest Ethiopia

Code	Description	Melkam	Teshale
P1	Thermal time from seedling emergence to the end of the juvenile phase (degree days)	352.8	369.2
P20	Critical photoperiod or the longest day length (hours) at which development occurs at a maximum rate	13.33	13.25
P2R	Phasic development leading to panicle initiation (degree days)	198.8	231.1
P3	Thermal time from end of flag leaf expansion to anthesis (degree days)	293.7	311.7
P4	Thermal time from anthesis to beginning of grain filling (degree days)	88.2	95.3
P5	Thermal time from beginning of grain filling to physiological maturity (degree days)	525.4	502.4
G1	Scaler for relative leaf size	4.4	2.9
G2	Scaler for partitioning of assimilates to the panicle (head)	6.2	6.3

Table 6. Comparison of observed and simulated phenology and growth of sorghum cultivars in Southwest Ethiopia during evaluation of DSSAT

Parameters	Cultivar	Observed	Simulated	RMSE	<i>d</i>
Days to anthesis		71	73	1.4	0.58
Days to maturity	Melkam	106	112	4.6	0.55
LAI (max)		4.54	4.71	0.57	0.61
Days to anthesis		76	77	1.7	0.61
Days to maturity	Teshale	114	117	2.9	0.57
LAI (max)		4.67	5.21	1.2	0.67

RMSE, root mean squared error; *d*, index of agreement; LAI (max), maximum leaf area index measured at the time of heading.

production of sorghum. Furthermore, disease and pest problem, poor extension services and market access, low purchasing power of input and the absence of weather information (data not shown) contributed to low productivity of sorghum in the region.

Discussion

Evaluation of models

Evaluation of the two models after calibration showed a good agreement between observed and simulated growth of sorghum. Simulations of seasonal soil water content, green canopy cover and dry aboveground biomass using AquaCrop and phenology, growth and development using DSSAT performed reasonably well. This was supported by an adequate level of statistical measures and a good fit of regression lines. The evaluation results

indicated also a good accuracy of the two models to predict grain yield of sorghum under water-limited conditions in Southwest Ethiopia. Previous studies showed that the simulation of sorghum yield in a water-limited environment using these models was promising (Hadebe *et al.*, 2017b; Sannagoudar *et al.*, 2019). Although the two models simulated grain yield reasonably well, AquaCrop relatively overestimated the grain yield as compared to DSSAT. This variation might be attributed to the differences on overall yield simulation process of the two models. AquaCrop simulates yield of crops in response to various degree of soil moisture availability as a function of water consumption where transpiration is first calculated and then translated into biomass through water productivity function. Finally, yield is derived from biomass and harvest index relations (Raes *et al.*, 2009; Steduto *et al.*, 2009). On the contrary, estimation of crop yield in DSSAT is a function of growth rate and duration (Tsuji *et al.*, 1998; White *et al.*, 2015). Growth rate involves mass

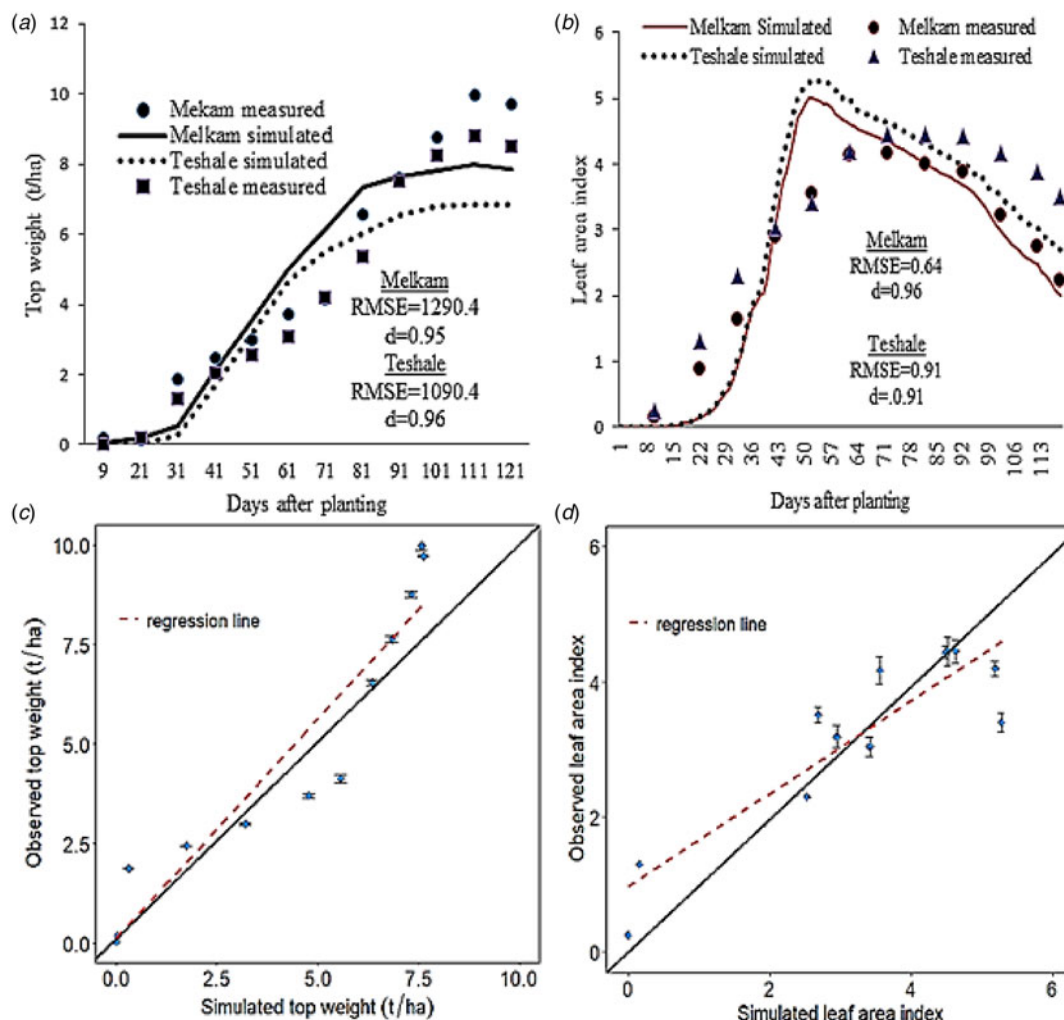


Fig. 4. Observed and simulated top weight (a) and LAI (b) of sorghum cultivars and regression between observed and simulated top weight (c) and LAI (d) of Melkam cultivar at Jinka during evaluation of DSSAT.

accumulation and area expansion that principally depends on amount of photosynthetically active radiation, temperature, nutrient and water availability. Growth duration involves phasic and morphological developments that are principally controlled by temperature. So, involving more number of processes in DSSAT than AquaCrop might have led to estimate yield relatively closer to the measured value.

Additionally, plant growth in DSSAT is governed by conversion of intercepted radiation to biomass during which the LAI is one of the key factors that determine the amount of light interception (Jones *et al.*, 2003). On the contrary, AquaCrop uses canopy cover to determine the amount of water transpired that later reflected on crop yield through its relation with biomass simulation (Steduto *et al.*, 2009). Accuracy of canopy cover estimates using digital image analysis limited by angle of view during aerial image capturing and canopy closure at later stage of crop growth resulting in saturation signal (Fiala *et al.*, 2006; Raj *et al.*, 2021). On the contrary, LAI estimates using a direct method as done in this study gives the most accurate values (Raj *et al.*, 2021). Hence, using LAI by DSSAT and canopy cover by AquaCrop as primary engine for capturing resources during the formation of biomass and subsequent yield might be additional reasons for variation in the accuracy of yield estimation between the two

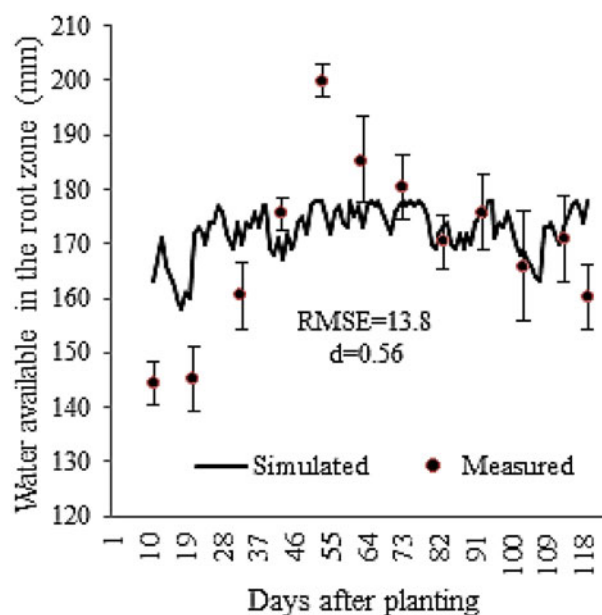


Fig. 5. Observed and simulated water available in the root zone at Jinka during evaluation of DSSAT. The vertical bars indicate \pm standard deviation ($n = 3$).

Table 7. Observed and simulated grain yields of sorghum cultivars and PBIAS (%) for simulation of grain yield during evaluation of AquaCrop and DSSAT in Southwest Ethiopia

Cultivar	Grain yield (t/ha)			PBIAS (%)	
	Observed	Simulated (AquaCrop)	Simulated (DSSAT)	DSSAT	AquaCrop
Melkam	4.2	5.1	4.6	-9.5	-21.4
Teshale	4.7	5.6	4.9	-4.3	-19.2

PBIAS, percent bias.

Table 8. Different yield levels of rainfed sorghum production in Southwest Ethiopia

Yield category (t/ha)	Benatsemay		Jinka		Mean
	Mean	CV (%)	Mean	CV (%)	
Actual yield ^a	1.51	40.3	1.51	40.3	1.5
Attainable yield ^b	3.06	30.8	3.06	30.8	3.06
Simulated water-limited yield					
AquaCrop	5.13	12.2	5.32	4.5	5.23
DSSAT	4.98	22.3	4.81	19.3	4.90

CV, coefficient of variation.

^aActual yield was considered for the period 2003–17 from Central Statistics Agency of Ethiopia. The actual yield and Y_w were averaged for the period 2003–17.

^bAttainable yield was average of 4 years (2014 to 2017). Simulated water-limited yield was averaged for the two cultivars over locations.

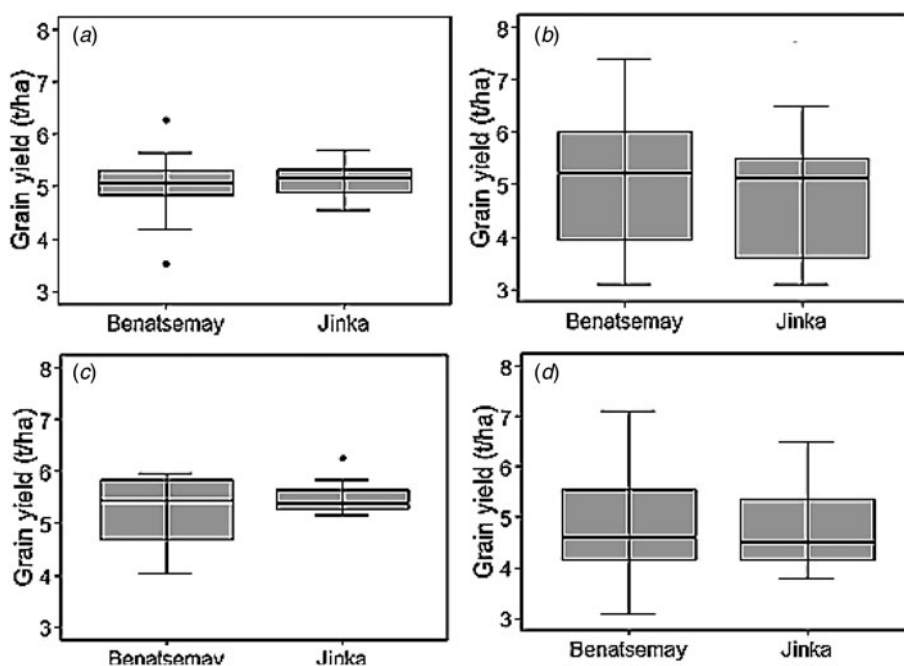


Fig. 6. Water-limited yield of Melkam (AquaCrop) (a), Melkam (DSSAT) (b), Teshale (AquaCrop) (c) and Teshale (DSSAT) (d) at two locations (Benatsemay and Jinka) in Southwest Ethiopia for the period 2003–17. Boxes indicate the lower and upper quartiles. The solid line within the box is the median. Whiskers indicate the minimum and maximum values and dots outside the whiskers are outliers.

models. Furthermore, DSSAT simulates a detailed plant and soil nutrient balance whereas AquaCrop simply evaluates crop response to different soil fertility regimes from poor to non-stress conditions (Jones *et al.*, 2003; Steduto *et al.*, 2009; Raes *et al.*, 2018). Consideration of nutrient balance instead of soil fertility regime is more realistic to see the effect of nutrients on plant growth and yield formation. Moreover, quantifying the effect of solar radiation in addition to water in DSSAT is likely to be an

additional advantage in estimating crop yield as close as possible to the measured value.

Yield levels, variability and gaps

During the targeted period, the actual yield of the crop showed an increasing trend. However, such a significant increment on the actual yield was accompanied by high year-to-year variability,

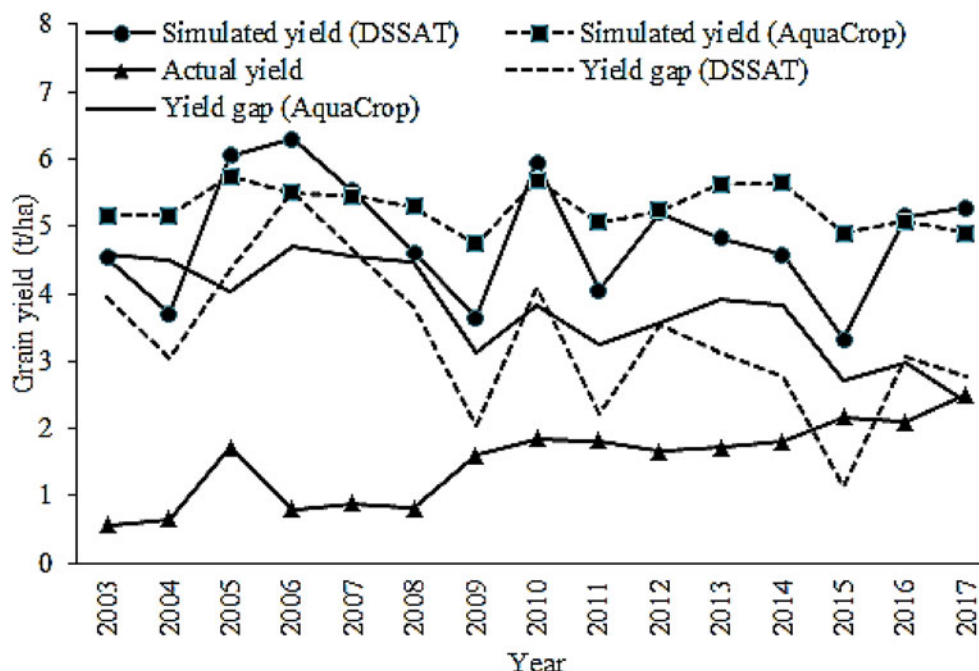


Fig. 7. Time series comparison of actual yield with water-limited yield and yield gaps (using DSSAT and AquaCrop) of rainfed sorghum production in Southwest Ethiopia. Actual yield was taken from CSA of Ethiopia for the period from 2003 to 2017. Simulated yield was average of Melkam and Teshale from the two sites (Jinka and Benatsemay) using DSSAT and AquaCrop for the period 2003–17.

Table 9. Existing yield gaps among actual, attainable and water-limited yield as simulated with AquaCrop and DSSAT for rainfed sorghum in Southwest Ethiopia

Yield comparison (t/ha) ^a	Benatsemay	Jinka
Attainable – actual yield	1.55	1.55
Water-limited yield (AquaCrop) – actual yield	3.62	3.81
Water-limited yield (DSSAT) – actual yield	3.44	3.23
Water-limited yield (AquaCrop) – attainable yield	2.07	2.26
Water-limited yield (DSSAT) – attainable yield	1.92	1.75

^aThe data represent the average yield gaps for the period 2003–17 except for attainable yield for which yield data was available for the years from 2014 to 2017.

which might be attributed to the existing variability of rainfall. This was confirmed by the existing correlation between growing season rainfall and annual actual yield of the region for the period 2003–17. The increase in actual yield could be the result of change in the adoption of improved agronomic measures in the region during the stated period although it is found at its early stage (Shiferaw and Yoseph, 2014; Yoseph and Sorsa, 2014).

Higher inter-annual variability of Melkam and Teshale Y_w was observed at Benatsemay than Jinka for both models and this could be attributed to differences in edaphic and climatic conditions of the area. For instance, the soil textural classes of Jinka and Benatsemay were clay loam and sandy loam, respectively. Such soil texture difference has a significant effect on availability of water and crop yield when water is the yield-limiting factor (Silungwe *et al.*, 2019). Similarly, the Y_w of the crop showed some differences with respect to the same yield level of other regions of Ethiopia where the potential yield of the crop was determined based on field experiment (5.15 t/ha) (Kinfе and Tesfaye, 2018) and crop model (2.8–10.2 t/ha) (Van Bussel

et al., 2015). Divergence of potential yield from field experiment and crop model is expected since under field conditions maintaining all management practices to their best level and controlling all biotic and abiotic factors throughout the growing season are quite difficult. Employing different models could be other source of variation during estimation of Y_w . For instance, during estimation of Sorghum Y_w in Global Yield Gap Atlas, Van Bussel *et al.* (2015) used WOFOST, which has a different approach to describe crop growth dynamics as compared to DSSAT and AquaCrop. Additionally, the Y_w of crops found to be different across different locations due to variation in growth duration and local weather conditions specially temperature and rainfall which do have significant direct and indirect effects on the crop growth and yield response (Deng *et al.*, 2019).

The attainable yield (3.06 t/ha) of the crop in the study area was lower than the same yield level of other sorghum producing areas of the country such as the 5.71 t/ha in Eastern Hararghe (Abady *et al.*, 2017; Abduselam *et al.*, 2018) and the 4.41 t/ha in Afar (Dilnesaw *et al.*, 2018), which could be due to local agro-ecological variation and the extent of harmonious application of agronomic practices (Fujimura *et al.*, 2010; Mundia *et al.*, 2019). Furthermore, the attainable yield was below the water-limited yield by 1.97 t/ha indicating existence of limitations in soil nutrients and water, which reduce sorghum yield performance in the area.

The average regional actual yield was below attainable and water-limited yield by 1.56 and 3.52 t/ha indicating loss of 51 and 70%, respectively. Such yield gaps are common under rainfed and subsistence farming system where crop production is constrained by water, nutrients and other environmental factors (Lobell *et al.*, 2009). This Y_g indicates the opportunity to enhance sorghum production by reducing the yield-limiting factors in the region. However, it is not possible to completely close the Y_g between actual yield and Y_w since the average yield of farmers would not reach to the ceiling of potential yield due to two main reasons (Van Ittersum *et al.*,

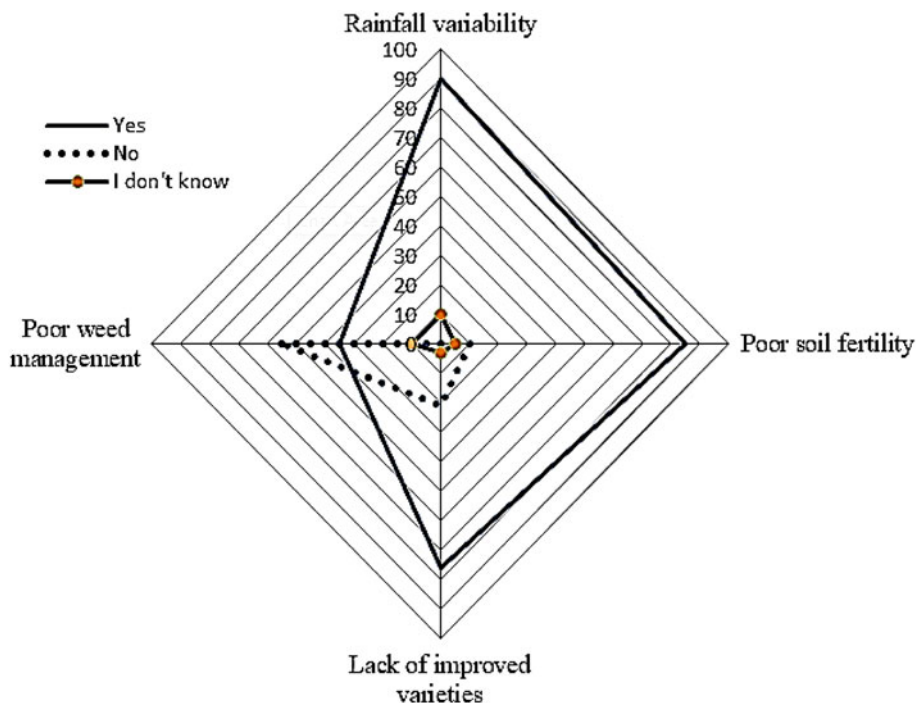


Fig. 8. Major sorghum production constraints identified by household heads (%) during the survey in 2018, Southwest Ethiopia.

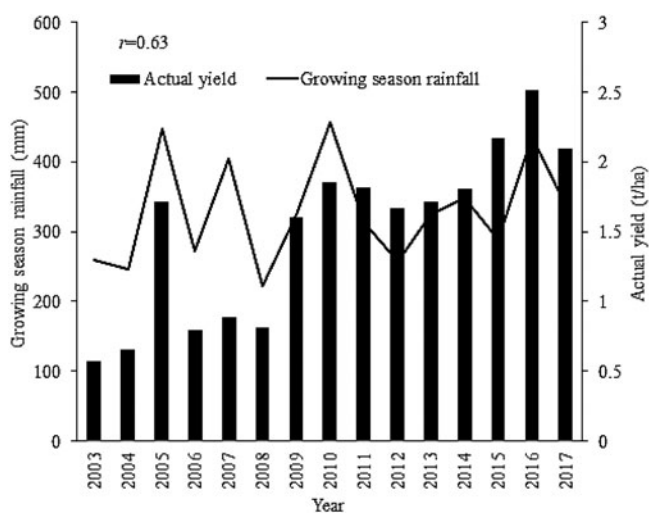


Fig. 9. Actual yield *v.* regional growing season rainfall for the period 2003–17 in Southwest Ethiopia. *r* is the correlation coefficient.

2013; Van Wart *et al.*, 2013a). First, there is a diminishing marginal yield benefit from application of additional input as yield approaches to the ceiling, and second, not all farmers in a given region have perfection on soil and crop management. Van Ittersum *et al.* (2013) asserted that average yield of farmers tend to plateau when they reach 75–80% of Y_p or Y_w and the exploitable yield gaps could be considered between average farm yield and 80% of Y_p or Y_w . Hence the exploitable yield gap of rainfed sorghum production in Southwest Ethiopia was 2.5 t/ha.

There was considerable variability on the existing Y_g between actual yield and Y_w of the crop within the 15 years of the targeted period. This could be attributed to differences in climatic conditions, management practices and adoption of improved

technologies. At later years of production, the yield gaps became narrowed compared to the earlier one's mainly because of an increment on average farmers yield due to adoption of improved technologies to some extent. Najafi *et al.* (2018) stated that crop productivity over time would be improved due to changes in technology and economic growth, improvement in input supply, release of new varieties and better agronomic practices. A trade-off exists between number of years considered for Y_g analysis and robust estimation of the Y_g with respect to environmental differences (Van Ittersum *et al.*, 2013; Van Wart *et al.*, 2013a). In favourable environments, the most recent 5–7 years are adequate for estimation of average farmers yield and simulation of Y_w with relatively low CV. On the contrary, 10–20 years are need to be considered in harsh environments having lower rainfall to compromise capturing adequate yield variability and avoiding the inclusion of climate change impact and adoption of technology. With this regard, the number of years considered in this study to estimate Y_g was adequate since it was conducted in rainfall-limited environments of Southwest Ethiopia.

Production constraints of sorghum

Exploring the underlying factors of yield gaps is very important to increase the future food production and closing the existing gaps (Meng *et al.*, 2013). A number of factors for existing sorghum Y_g in Southwest Ethiopia were identified during the survey from which rainfall variability, poor soil fertility, lack of improved varieties and poor weed managements were the major ones. These production constraints are commonly experienced by other sorghum producing area of Ethiopia (Schneider and Anderson, 2010; FAO and DWFI, 2015). Similarly, in sub-Saharan Africa sorghum is considered as poor-man crop and its production has been carried out in marginalized areas with no or low inputs and improved agronomic practices, poor extension services and market linkage (Tonitto and Ricker-Gilbert, 2016).

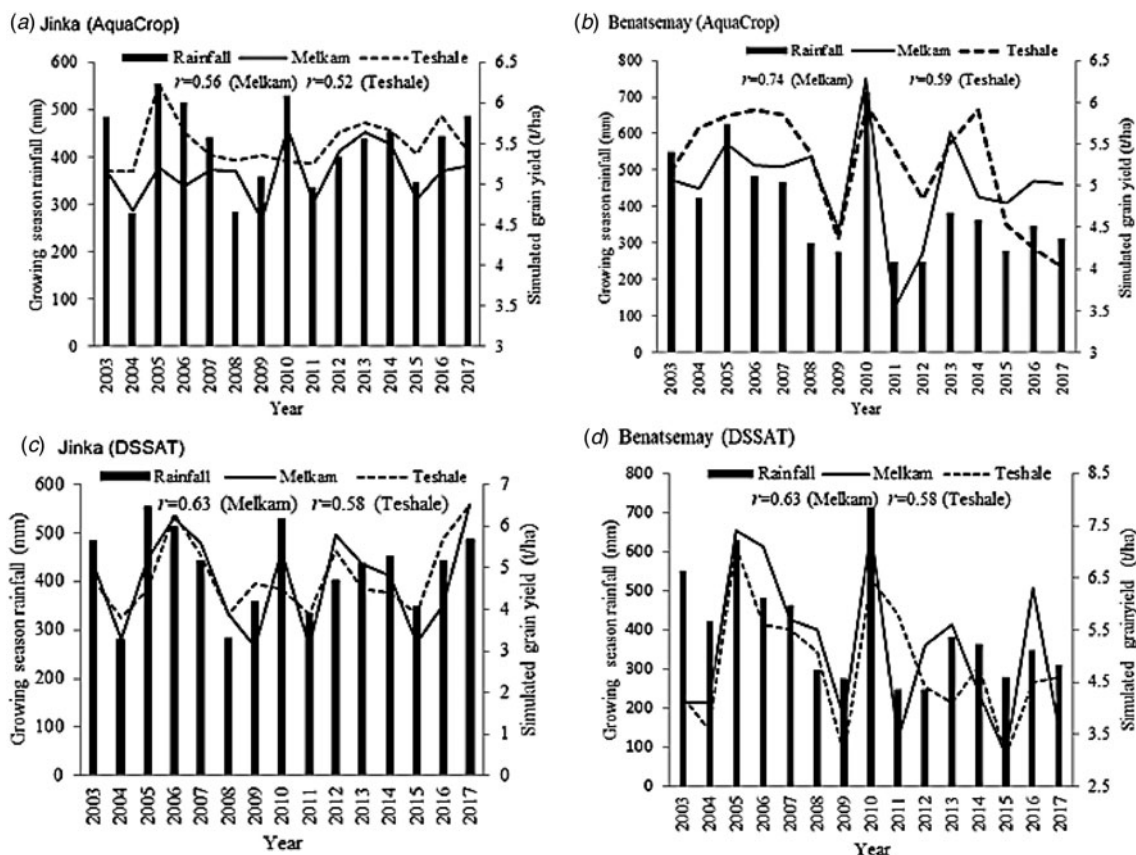


Fig. 10. Growing season rainfall v. simulated water-limited yield of sorghum cultivars: (a) simulation with AquaCrop at Jinka, (b) simulation with AquaCrop at Benatsemay, (c) simulation with DSSAT at Jinka and (d) simulation with DSSAT at Benatsemay, in Southwest Ethiopia. *r* is the correlation coefficient.

Table 10. Comparison of grain yield (t/ha) response of sorghum cultivars with and without fertilizer (NPSB) application in southwest Ethiopia

	Number of samples	Unfertilized plot (0 kg/ha)	Fertilized plot (150 kg/ha)	<i>t</i> test ($\alpha = 0.05$)
Melkam	6	2.78	4.91	0.01
Teshale	6	2.93	5.31	0.03

Even though sorghum is one of most important crops in a harsh environment, the adverse weather conditions particularly rainfall during the growing season penalize farmers yield (Singh *et al.*, 2014; Msongaleli *et al.*, 2017; Zewdu *et al.*, 2020). There has been a consistent effort on developing improved varieties in Ethiopia but they do have little adoption by the farmers due to poor extension service, bird attack specially for early maturing varieties, higher post-harvest loss due to pest and lower biomass as compared to the land races (Beshir and Sime, 2013; Kinfe and Tesfaye, 2018). Additionally, economical problem related to lower market prices of grain as compared to other cereals and higher input prices such as chemical fertilizers demotivated farmers to use the improved agronomic practices during sorghum production (Tonitto and Ricker-Gilbert, 2016). Under such situations closing the Y_g by achieving 80% of Y_w needs a big effort involving supply of improved seeds, chemical fertilizers and pesticides, effective weeds and pest management schemes, adoption of

recommended agronomic practices and access to timely weather information (Deng *et al.*, 2019).

Conclusions

Calibration and evaluation results of AquaCrop and DSSAT showed that observed and simulated soil and crop parameters were in good agreement. The yield gaps between actual and water-limited yield simulated using DSSAT and AquaCrop ranged from 1.2 to 5.5 t/ha and 2.4 to 4.7 t/ha, respectively indicating the presence of 3.53 t/ha actual and 2.5 t/ha exploitable yield gaps in the region. Seasonal rainfall variability, poor soil fertility, lack of improved varieties and poor weed managements were the major production constraints of sorghum in Southwest Ethiopia. The existing yield gap could be managed by employing classic agronomic practices and technologies with the participation of different stakeholders. However, these classic agronomic practices and improved technologies would not be realized by subsistence farmers in Southwest Ethiopia particularly and Ethiopia generally unless effective technical and economic support goes to these farmers.

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Conflict of interest. The authors declare that there are no conflicts of interest.

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