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Yield Gap and Its Spatial Variation for Bread Wheat and Malt Barley Production in Southeastern Ethiopia: A quantitative Analysis Using Crop Simulation model

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Abstract

Despite the extensive area coverage of cereals in Ethiopia, their national productivity is below the average for world yield productivity. Analyzing the yield gap, i.e. the difference between yield potential and the actual yield is essential to explore intervention options that can minimize the yield gap. Therefore, this paper is aimed at estimating the yield gap and mapping its spatial variation for bread wheat and malt barley production in southeastern parts of Ethiopia. The process-based Decision Support System for Agro-technology Transfer (DSSATv4.7.5) crop model was calibrated for two wheat varieties (Hidase and Ogolcho) and one barley variety (Ibon) and used to estimate the potential yield. Potential yield was calculated for each selected reference weather station, and compared with the corresponding actual yields achieved by farmers averaged at district level to estimate the yield gap. The model simulated the highest potential yields of 7 and 6.3 t/ha respectively for the Hidase and Ogolcho varieties at the Dinsho site. In contrast, the lowest yield was simulated at Ziway-Dugda (4.9 t/ha) for Hidase and Merti (4.4 t/ha) for Ogolcho varieties. Moreover, the highest yield gap (78%) was determined at Amigna and the lowest yield gap (26%) was determined at Lemu and Bilbilo district for malt barley. Generally, the yield gap analysis revealed high yield gaps and spatial variation across study sites for both crops.

Keywords: Bread Wheat; Crop Model; Malt Barley; Model Calibration; Southeastern Ethiopia; Yield Gap

Abbreviations

EMI: Ethiopian Meteorology Institute; EIAR: Ethiopian Institute of Agricultural Research; YP Yield potential; DSSAT: Decision Support System for Agro-technology Transfer; NVTs: National Variety Trials; KARC: Kulumsa Agricultural Research Center; GLUE: Generalized Likelihood Uncertainty Estimation.

Introduction

In Ethiopia, cereals are the major food crops both in terms of the area they covered (82%) and volume of production (88.7%) within the category of grain crops [1]. They are the principal staple crops and produced in larger volume compared with other crops. Wheat is one of the major staple and strategic food security crops, covering 1.9 million hectares of land and average productivity of 3.1 t/ha [1]. Barley has production of 2.1 million tonnes with average productivity of 2.6 t/ha while its area coverage is 0.8 million hectares in the country [1].

Knowing the gap between the potential and actual yield has various applications. It helps to formulate the agricultural policy and prioritize the research and extension works [2]. Information on the yield gap spatial variability is also useful to develop a region, field or site specific recommendations, including 'real time' adjustments to management practices in response to weather events that change yield potential in a given season [2].

Yield potential (Yp) is the ideal yield of a crop cultivar when grown in environments to which it is adapted, with unlimited nutrients and water and with effectively controlled pests and diseases [3]. Potential yield can be estimated by conducting field experiments under well-managed, controlled conditions to restrict any limitations to yield. In such experiments, factors other than climate should not limit the potential yield of any crop variety. However, omitting any factor that limits and reduces growth and yield under field conditions is a challenging task. Using process-based crop simulation models is an alternative method to estimate potential yield. The model can quantify the magnitude and variability of the potential yield by taking into account temporal variations of weather conditions and interactions with the environment and management. Actual yield (Ya) is the yield achieved in a specific year or period with current production techniques and management at a farm or regional level.

The difference between yield potential and the actual yield achieved by farmers represents the exploitable yield gap [4]. To explore adaptation options that can minimize the yield gap, analyzing the yield gap, i.e. the difference between potential and actual yields is very important. The yield gap concept has been applied in many studies [5-9] as an indicator for the possibility to increase crop yields in a given region. Identifying the essential factors of yield gaps is necessary to increase future food production capacity and to help formulate policies. Crop models can provide reasonable estimates of yield potential when historical weather data are available [10]. Crop simulation models can be used to estimate Yp and Yw based on current management, genetic features of the crop, weather and water supply.

There are different types of yield gaps analysis. The first type can be described as 'broad scope, low detail' on causes. A broad scope in terms of crops, uses large spatial coverage and less focus on identification of causes of yield gaps. A second type is 'narrow scope, more detail'. A narrow focus, uses limited spatial coverage, and with much more detail on identification of causes for closing the yield gap. It is easier to derive more specific policy recommendations from such studies because they do provide information about the causes of yield gaps, which can include biophysical constraints such as abiotic/biotic stresses, crop management practices, socio-economic constraints etc. Once specific causes of yield gaps have been identified, the priorities follow directly from the analysis: priority must be given to addressing those factors contributing most to large yield gaps. Prioritization can be further refined with information on which causes of yield gaps can more easily be resolved and which ones are very hard to resolve based upon available technologies and expected cost-benefit ratios. Therefore, the objective of this research paper is to analyze the exploitable yield gap, and map its spatial variation for bread wheat and malt barley production in southeastern Ethiopia.

Materials and Methods

Description of the study area

The study was conducted in selected wheat belt areas of the southeastern parts of Ethiopia including Arsi, West Arsi and Bale zones located between 5 and 9° N latitude and 38 and 41° E longitude at altitudes ranging from 1600 to 3200 m.a.s.l. (Figure 1). The selected sites represent different agro ecologies (lowland, midland and highland) areas.

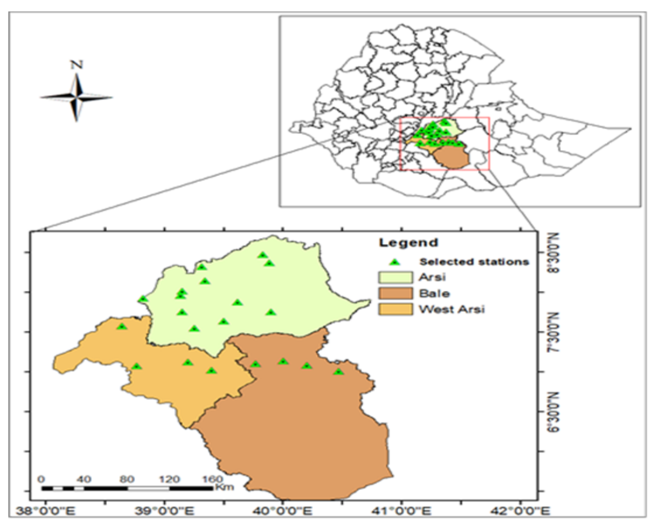

Figure 1: Location map of the study area.

The rainfall regime over much of the southeastern and central highlands is typically bimodal, with the main rains, known as the Meher season, occurring from June through to September, and the short rains, known as the Belg season, occurring during February to May. The Belg rains are not sufficiently reliable to permit crop planting each year, and when they do occur, they can merge into the Meher. The mean annual rainfall in the southeastern parts of Ethiopia ranges from 600 to 2000 mm depending on altitude. The weather data used in these analyses was obtained from the Ethiopian Meteorology Institute (EMI) and Ethiopian Institute of Agricultural Research (EIAR).

The soils of southeastern highlands in general, are dominated by Luvisols, Vertisols and Acrisols. Vertisols with high water retention capacity are dominant soils at some highland areas while Luvisols and Acrisols are dominant at most of the sites [11].

Soil information in Africa in general and particularly in Ethiopia has been fragmented and limited to specific zones of interest [12]. The soil profile data used in these analyses was obtained from the African Soil Information Service (AfSIS) at 250 m resolution [13].

Crop model calibration

Calibration of crop model is standard practice, and it involves estimation of crop parameters based upon observed field data. It is the process of estimation of unknown parameters using practical observations. Calibration is an important part of the modeling process, since it enables the numerical model results and their reliable use in model applications. Essentially, model calibration involves adjusting model parameters to reduce the error between the model results and the measured data. Calibration is often necessary because parameter values are usually not universally valid, as explained in the context of crop models.

The Decision Support System for Agro-technology Transfer (DSSAT) version 4.7.5 was used in this study. The model was calibrated and evaluated with independent field data sets (that included phenology and yield) under normal conditions. The crop information and management data were collected from the national variety trials (NVTs) in 2013-2016 experimental years conducted at Kulumsa Agricultural Research Center (KARC) experimental site for wheat varieties and at Bekoji experimental site for malt barley variety in 2015-2018 experimental years. The Generalized Likelihood Uncertainty Estimation (GLUE) program was used to estimate genotype-specific coefficients for the DSSAT crop models. It is a Bayesian estimation method that uses Monte Carlo sampling from prior distributions of the coefficients and a Gaussian likelihood function to determine the best coefficients based on the data that are used in the estimation process. Two bread wheat varieties Hidase and Ogolcho, and one malt barley variety Ibon were calibrated for this specific study.

The data included days to heading, days to physiological maturity and grain yield. The phenology coefficients P1V, P1D and P5 as well as the yield coefficients G1, G2, G3 and PHINT were calibrated so the observed and simulated phenological dates and grain yield were as close as possible for each bread wheat and malt barley variety.

Model performance evaluation

Model evaluation was performed to determine whether the calibrated crop model was capable of reproducing the available observations at the study locations. Independent experimental data was used for the model validation and performance evaluation. The experimental crop phenology and yield data recorded at Kulumsa in 2017/18-2019/20 for Hidase (ETBW 5795) and in 2017/18-2018/2019 for Ogolcho (ETBW 5520) were mixed up with other data sets recorded at agro-ecologically different experimental site (Asasa), and used for model evaluation for wheat varieties. Similarly, the experimental data recorded at Bekoji site in 2019/20 and 2020/21 experimental years together with different data collected from another experimental site (Kofele) was used for model evaluation for malt barley variety. The performance indicators such as Root Mean Square Error (RMSE), Coefficient of Determination (R2) normalized root mean standard error (RMSEn) and the index of agreement (d) for each variety were computed and used to evaluate the model prediction capability (Equations 1, 2 and 3).

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}\left(P_i - O_i\right)^2} \quad (1)$$

Where n is the number of observations, Pi and Oi are predicted and observed values respectively

$$R^2 = \frac{SS\left(regrassion\right)}{SS\left(residual\right)} \quad (2)$$

Where, SS (regression) is sum squared regression and SS (residual) is sum squared residual

$$d = 1 - \left[\frac{\sum_{i=1}^{n}\left(P_i - O_i\right)^2}{\sum_{i=1}^{n}\left(\left|P'_i\right| + \left|O'_i\right|\right)^2}\right], 0<d<1 \quad (3)$$

Where n is the number of observations, Pi is the predicted value for the ith measurement, Oi is the observation for its measurement, M is the mean of the observed variable, P'i = Pi −M and O'i = Oi−M. The d-statistic and coefficient of determination (R2) values are closer to unity and lower values of RMSE indicate a good agreement between the observed and simulated results which shows good performance of the model.

Yield Gap Estimation

An average yield (Ya) which is achieved in a farmer's field was obtained from the agricultural Bureaus of Arsi, west Arsi, and Bale zones. To represent variation in time and space in the study area, the average yield (in space and time) achieved by farmers in the region under the most widely used management practices (sowing date, cultivar maturity, plant density, nutrient management, and crop protection) was used. Ten years of average actual yield data were utilized to compromise between variability in yields and the necessity to avoid confounding effects of temporal yield trends due to technological or climate change. The calibrated and evaluated crop model was used to simulate potential yield for each corresponding year under water and nutrient-unlimited, and optimum crop management conditions. The model simulated ten years of potential yield were averaged and used to estimate the yield gap between potential and actual yields for each reference weather station.

The yield gap, the difference between potential yield (model simulated) and actual yield (obtained from zonal bureaus of agriculture) was quantified by subtracting the actual yield from the potential yield for each selected reference weather station. About twenty reference weather stations were selected from twenty districts based on the availability of actual yield data and weather data for this yield gap analysis.

$$YG\% = \frac{PY - AY}{PY} x100\% \quad (4)$$

Where YG is yield gap, PY is potential yield and AY is actual yield.

	Asasa soil data								Kofele soil data							
Depth	Clay%	Silt%	San%	OC%	PH	CEC	TN%	BD	Clay%	Silt%	San%	OC%	PH	CEC	TN%	BD
5	36.3	31.8	32	3.32	6.8	33.1	0.308	1.22	35.9	37.3	26.8	5.21	6.1	26	0.436	1.1
15	35.9	32.1	32	2.14	6.9	33.7	0.211	1.24	36	36.1	27.9	3.09	6.1	25.5	0.245	1.11
30	40.4	30	29.6	1.63	6.9	32.7	0.178	1.25	39.8	34.4	25.8	2.04	6.2	25	0.222	1.11
60	41.3	29.5	29.2	1.07	7.2	31.7	0.111	1.27	43	32.7	24.3	1.43	6.2	23.9	0.167	1.14
100	41.2	29.7	29.1	0.68	7.3	31.8	0.088	1.27	47.3	30.3	22.4	0.83	6.2	23.5	0.104	1.16
200	38.9	30.7	30.4	0.41	7.4	32.3	0.066	1.28	48.2	28.9	22.9	0.58	6.3	23.6	0.077	1.18
	Bekoji soil data								Kulumsa soil data							
Depth	Clay %	Silt%	Sand%	OC%	PH	CEC	TN%	BD	Clay%	Silt%	Sand%	OC %	PH	CEC	TN%	BD
5	33.9	37.4	28.7	5.38	5.9	30.3	0.404	1.07	41.7	27.5	30.8	3.57	6.5	38.4	0.254	1.18
15	33.8	37.1	29.1	3.14	5.9	29.4	0.25	1.1	42.2	26.9	30.9	2.48	6.5	38.3	0.188	1.21
30	36.8	35.6	27.6	2.09	5.8	28.2	0.209	1.15	42.7	26.6	30.7	1.78	6.6	38.4	0.145	1.26
60	46.5	30.8	22.7	1.59	5.8	28	0.143	1.2	42.4	25.6	32	1.22	7	40.3	0.101	1.24
100	49	29.5	21.5	1.12	5.9	27.7	0.093	1.23	36.8	25.7	37.5	1.02	7.5	41.3	0.075	1.23
200	50	29.6	20.4	0.83	6.1	27.6	0.061	1.24	40.4	26.2	33.4	0.42	7.8	40.2	0.041	1.23

Source: Africa soil profiles (legacy) database (Leenaars, 2014).

Table 1: Soil profile data used for model calibration and evaluation.

Results and Discussion

Calibration of Crop Model

The results showed that the model simulated values were very close to the observed data for both phenology and grain yield parameters for all varieties which indicated good performance of the model (Table 3). The genetic coefficients used in CERES-wheat model to characterize the growth and development of wheat and barley varieties are presented in Table 2.

Coefficients	Definition	Wheat		Barley
		Hidase	Ogolcho	Ibon
P1V	Days, optimum vernalizing temperature, required for vernalization	12	8	5
P1D	Photoperiod response (% reduction in rate/10 h drop in pp)	33	35	18
P5	Grain filling (excluding lag) phase duration (degree day)	306	430	538
G1	Kernel number per unit canopy weight at anthesis (#/g)	29	27	18
G2	Standard kernel size under optimum conditions (mg)	23	23	47
G3	Standard, non-stressed dry weight (total, including grain) of a single tiller at maturity (g)	1.5	1.4	1
PHINT	Thermal time between the appearance of leaf tips (degree days).	86	95	96

Table 2: Genetic coefficients used to characterize the growth and development of wheat and barley Varieties

Crop	Variety	Experimental	Days to heading		Days to maturity		Grain yield (kg/ha)	
		Year	Simu.	Obser.	Simu.	Obser.	Simu.	Meas.
Wheat	Hidase	2013	65	65	120	122	4974	5140
		2014	60	56	114	114	4723	4580
		2015	59	57	111	113	5122	5222
		2016	62	62	114	114	5392	5312
	Ogolcho	2013	70	72	126	126	3848	3594
		2014	60	59	125	122	4367	4165
		2015	61	60	120	120	4499	4653
		2016	70	67	121	118	5356	5570
	Ibon	2015	82	80	146	146	6413	6216
Barley		2016	80	78	141	139	4927	5244
		2017	93	93	154	152	4533	4562
		2018	95	97	141	141	6255	6242

Table 3: Comparison between observed and simulated parameters after model calibration for wheat and barley.

Model Performance Evaluation

The test statistics indicated a good ability of the model to predict days to heading, days to physiological maturity and grain yield for both crops, thus the calibrated and evaluated model can be used for further analysis (Table 4).

Crop	Variety	Experiment Site	Experimental Year	Days to heading		Days to maturity		Grain yield(kg/ha)	
				Simu.	Obser.	Simu.	Obser.	Simu.	Meas.
Wheat	Hidase	Asasa	2013	70	67	123	124	3163	3255
		Asasa	2014	67	66	118	116	3704	3977
		Asasa	2015	64	63	114	110	3550	3751
		Asasa	2016	70	66	119	121	3933	3863
		Kulumsa	2017	66	64	113	110	5998	6077
		Kulumsa	2018	73	73	116	116	5168	5128
		Kulumsa	2019	80	82	132	136	5446	5580
	Ogolcho	Asasa	2013	64	64	120	120	2894	2692
		Asasa	2014	63	64	114	112	3368	3357
		Asasa	2015	70	68	111	111	3357	3467
		Asasa	2016	72	72	125	127	3695	3662
		Kulumsa	2017	68	67	119	118	4367	4410
		Kulumsa	2018	66	66	114	116	4683	4373

Barley	Ibon	Kofele	2015	84	83	153	150	5674	5443
		Kofele	2016	80	83	146	146	4671	4639
		Kofele	2017	86	84	144	140	4042	3836
		Kofele	2018	76	72	136	136	4579	4537
		Bekoji	2019	106	108	138	140	7182	7392
		Bekoji	2020	80	78	144	144	3446	3260

Table 4: Observed and simulated parameter values used for wheat and barley model evaluation

Crop	Variety	Parameters	*Simul*	*Obser*	*RMSE*	*RMSEn*	R^2	*d-stat*
Wheat	Hidase	Days to heading	70.57	68.71	3.38	4.93	0.9	0.87
		Days to maturity	119.29	119	5.2	4.37	0.96	0.9
		Grain yield	4423.14	4518.71	215.24	4.76	0.97	0.89
	Ogolcho	Days to heading	68.5	66.83	3.9	4.96	0.91	0.84
		Days to maturity	117.17	117.33	2	1.56	0.93	0.84
		Grain yield	3727.33	3660.17	275.49	9.75	0.88	0.74
Barley	Ibon	Days to heading	85.33	84.67	6.26	7.54	0.85	0.91
		Days to maturity	143.5	142.67	5.35	3.75	0.88	0.82
		Grain yield	4932.33	4851.17	338.55	6.98	0.96	0.98

Table 5: Model performance evaluation parameters for wheat and barley.

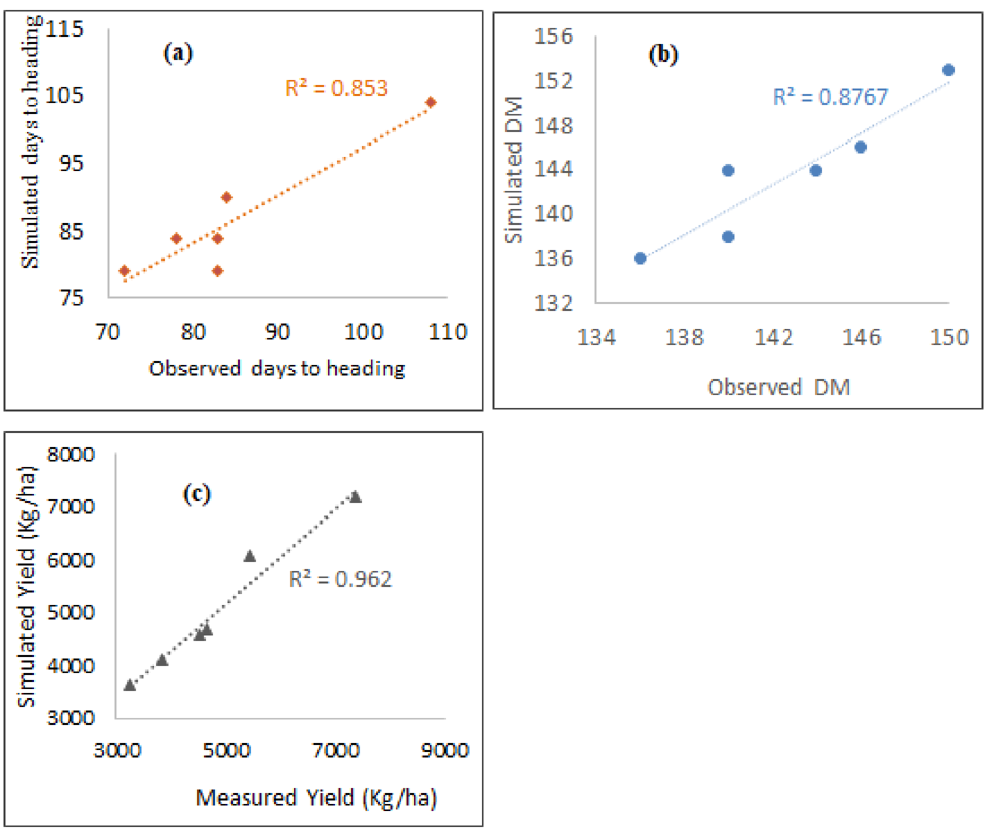

Figure 2: Observed versus Simulated graphs of (a) days to heading, (b) days to physiological maturity and (c) grain yield for malt barley

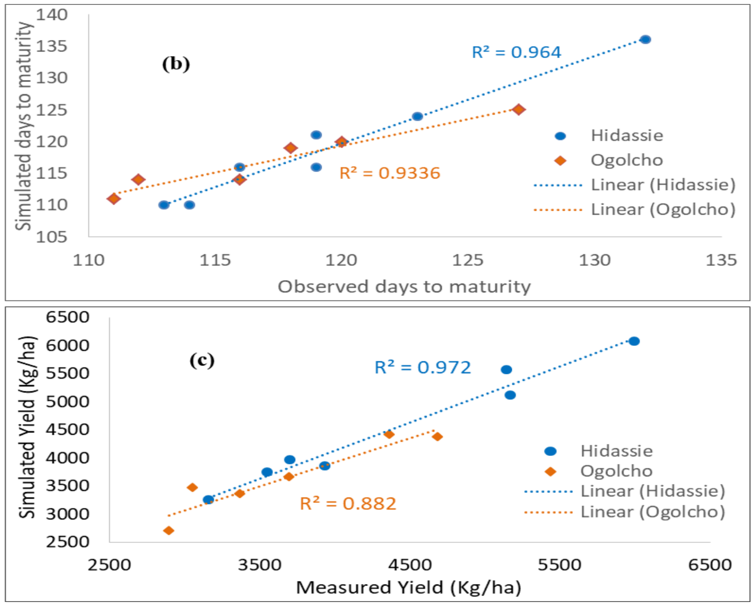

Figure 3: Observed versus Simulated graphs of (a) days to heading, (b) days to physiological maturity, and (c) grain yield for wheat varieties

Yield gap analysis and its spatial variation

Bread Wheat: Yield potential (Yp), also called potential yield, is the yield of a crop cultivar when grown with non-limiting water and nutrients and biotic stress effectively controlled [3]. When the crop is grown under conditions that can achieve Yp, the growth rate is determined only by solar radiation, temperature, atmospheric CO2 and genetic traits that govern length of growing period (called cultivar or hybrid maturity) and light interception by the crop canopy (e.g., canopy architecture). Potential yield is location specific because of the climate, but in theory not dependent on soil properties assuming that the required water and nutrients can be added through management.

The yield gap between potential yield (model simulated) and actual/average yield (obtained from zonal bureaus of agriculture) was quantified for each selected reference weather stations. About twenty reference weather stations were selected from twenty districts based on the availability of actual yield data and weather data, and considered in this yield gap analysis.

Average yield (Ya) is the yield actually achieved in a farmer's field. To represent variation in time and space in the study area, the average yield (in space and time) achieved by farmers in the region under the most widely used management practices (sowing date, cultivar maturity, and plant density, nutrient management and crop protection) was used. Ten years actual yield data was utilized for estimating Ya to compromise between variability in yields and the necessity to avoid confounding effects of temporal yield trends due to technological or climate change. Similarly, potential yield was simulated for each corresponding year and averaged to obtain the yield gap between potential and actual yields for each reference weather station.

The model simulated the highest potential yields 7.0 and 6.3 t/ha, respectively for Hidase and Ogolcho varieties at Dinsho site while the lowest yield was simulated at Ziway Dugda (4.9 t/ha) for Hidase and at Merti (4.4 t/ha) for Ogolcho varieties (Table 6). The analysis result revealed that there was high bread wheat yield gap, and its variation across the study sites is also very high. The highest yield gap for Hidase and Ogolcho varieties are 67 and 64%, respectively, and both are determined at Robe Arsi district. The lowest yield gap is 22 and 13% determined at Gadab Asasa district for Hidase and Ogolcho varieties, respectively. Overall, yield gap across the study area is highly variable which is ranged from 22 to 67% for Hidase and 13 to 64% for Ogolcho varieties. This might be due to the variability of soil fertility and weather parameters in the study area. However, irrespective of these limiting factors, there is high wheat production potential in the selected study sites of different agroecologies (lowland, midland, and highlands). Therefore, it could be concluded that closing the yield gap between potential and actual yield is possible through managing those nutrient and water-related limiting factors. This means identifying the best intervention options is essential to minimize the gap between potential and actual yields in the study area. The quantified yield gap in tons per hectare and its spatial distribution are depicted in Figure 4 (a) and (b) for both wheat varieties.

		Hidase Variety				Ogolcho Variety			
S. No.	**District Name**	**PY (t/ha)**	**AY (t/ha)**	**YG (t/ha)**	**YG (%)**	**PY (t/ha)**	**AY (t/ha)**	**YG (t/ha)**	**YG (%)**
1	Adaba	6.8	4.7	2.1	30	5.8	4.7	1.1	19
2	Amigna	5.7	2.3	3.4	59	5.1	2.3	2.7	54
3	Negele Arsi	5.5	3	2.5	45	5	3	2	40
4	Robe Arsi	6.3	2.1	4.2	67	5.8	2.1	3.7	64
5	Assela town	6.5	4.6	1.9	30	5.8	4.6	1.2	21
6	Bale Robe town	5.4	3.8	1.6	29	5	3.8	1.1	23
7	Digelu_Tijo	6.5	3.7	2.8	43	5.8	3.7	2.1	37
8	Dinsho	7	3	4	57	6.3	3	3.3	52
9	Dodota	6.4	2.7	3.7	57	5.7	2.7	3	52
10	Gadab_Asasa	5	3.9	1.1	22	4.5	3.9	0.6	13
11	Goro	6.4	2.8	3.7	57	5.9	2.8	3.1	53
12	Guna	5.5	2.1	3.4	62	5.2	2.1	3.1	59
13	Kofele	5.4	4	1.4	26	4.7	4	0.7	15
14	Lemu_Bilbilo	6.6	3.9	2.6	40	5.5	3.9	1.6	29
15	Lode_Hetosa	5.7	3.8	1.8	32	5.2	3.8	1.3	26
16	Merti	5	1.9	3.1	61	4.4	1.9	2.5	56
17	Shirka	6.3	3.2	3.1	49	5.8	3.2	2.6	45
18	Sinana	6.4	3.8	2.6	40	5.9	3.8	2.1	35
19	Tiyo	6.4	4.6	1.8	29	5.8	4.6	1.2	20
20	Zeway Dugda	4.9	2.5	2.4	49	4.9	2.5	2.4	49

Table 6: Hidase Variety & Ogolcho Variety.

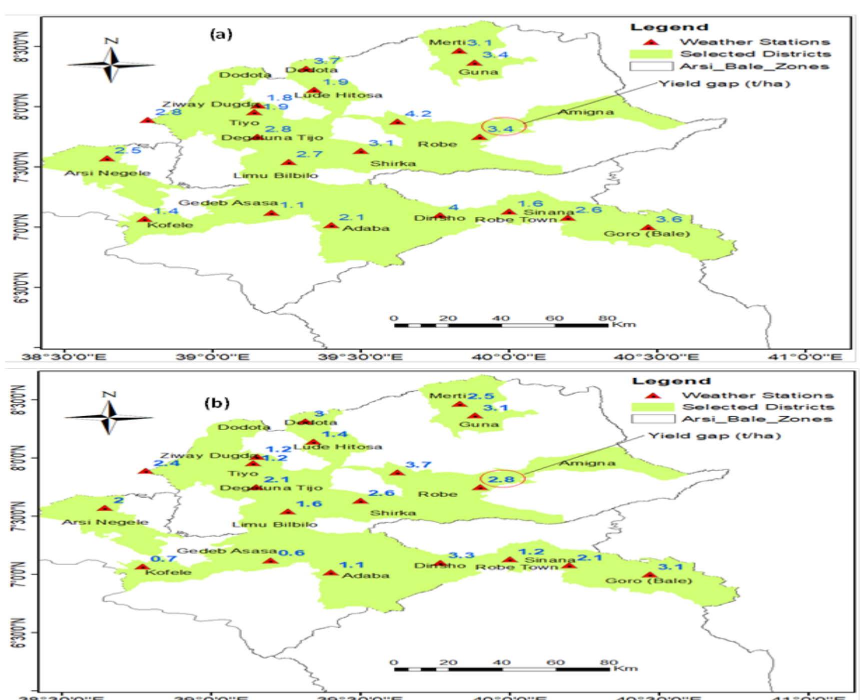

Figure 4: Quantified yield gap distribution for (a) Hidase; (b) Ogolcho varieties of bread wheat.

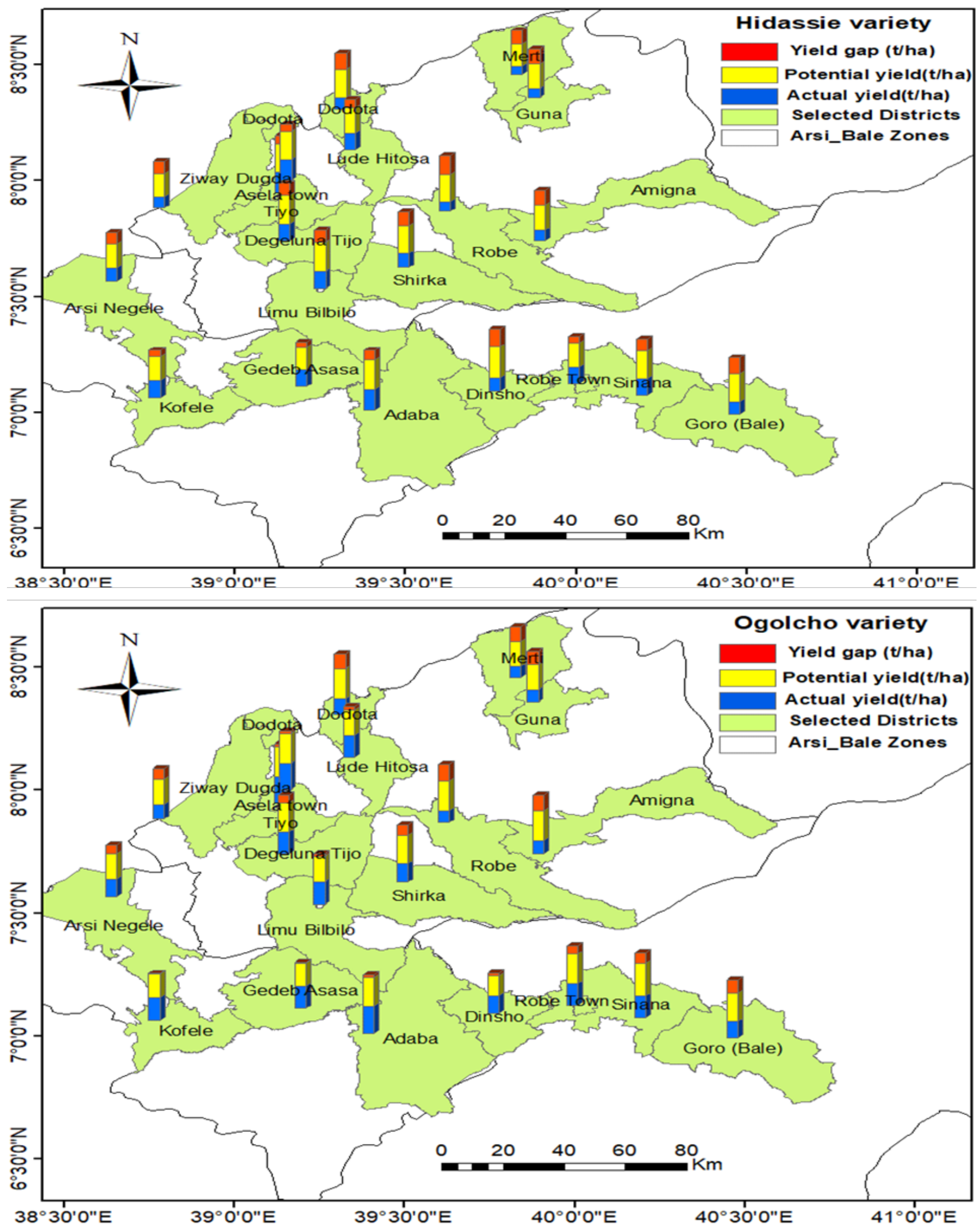

Figure 5: Graphical representation of yield gap distribution for Hidase and Ogolcho varieties of bread wheat.

Malt barley: The potential yield, actual yield and percentage yield gap for malt barley is presented in table 7. The highest yield gap percentage (78%) was determined at Amigna district while the lowest percentage (26%) was determined at Lemu and Bilbilo district for malt barley production. Yield gap variation across the study sites is relatively low while the percentage yield gap is higher for malt barley as compared to that of bread wheat. This indicated that, the area has high production potential for malt barley whereas the current production is below half in most of the selected study sites. Thus, identifying intervention options that can minimize the gap between potential and actual yield is very important to improve malt barley production in the study area. The quantified yield gap and its spatial variation for malt barley are depicted in Fig. 6.

S. N.	District Name	Latitude	Longi-tude	Altitude	PY (t/ha)	AY (t/ha)	YG (t/ha)	YG (%)
1	Adaba	7.017	39.4	2420	7.1	3.1	4	56
2	Amigna	7.75	39.9	2466	10.3	2.3	8	78
3	Negele Arsi	7.574	38.644	1960	3.9	2.9	1	26
4	Robe Arsi	7.876	39.622	2441	4.9	2.1	2.8	57
5	Assela Town	7.956	39.138	2413	10.5	4.6	5.9	56
6	Bale Robe Town	7.13	40	_	7.9	2.9	5	63
7	Digelu Tijo	7.75	39.15	_	10.3	3.7	6.6	64
8	Dinsho	7.1	39.767	3072	5.2	2.9	2.3	45
9	Gadeb Asasa	7.119	39.199	2340	4.8	3	1.8	37
10	Goro	7	40.47	1800	4.3	2.4	1.9	45
11	Guna	8.367	39.883	2531	3.6	2.1	1.5	42
12	Kofele	7.07	38.77	2620	5.8	3.4	2.4	41
13	Lemuna Bilbilo	7.543	39.255	2780	5.3	3.9	1.4	26
14	Lode Hetosa	8.142	39.342	2044	5.4	3.8	1.6	30
15	Merti	8.467	39.833	1630	3.8	1.9	1.9	50
16	Shirka	7.633	39.5	2400	7.8	3.2	4.6	59
17	Sinana	7.08	40.2	_	9.9	2.9	7	71
18	Tiyo	8.01	39.155	2211	9.5	4.6	4.9	51

Table 7: Potential yield, actual yield and percentage yield gap for malt barley.

Conclusion

Information on the yield gap spatial variability is useful to develop a region, field or site specific recommendations, including 'real time' adjustments to management practices in response to weather events that change yield potential in a given season. The assessment of yield potential and yield gap can help identify limiting factors and develop strategies to improve crop productivity and to increase future food production capacity. In this study, the yield gap i.e. the difference between potential and actual yield was quantified, and its spatial variability was also mapped for bread wheat and malt barley production. The analysis revealed that the yield gap and its spatial variability is very high across the study sites for both crops. This high yield gap spatial variability indicated site specific recommendations are required to close the gap between potential and actual yields. Thus, conducting further study to identify the major causes/factors of yield gap and intervention options that can minimize the yield gap is essential in improving bread wheat and malt barley production and productivity of the study area.

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