Received: 17 December 2020 | Accepted: 20 September 2021 | Published online: 8 November 2021

DOI: 10.1002/agj2.20900

Agronomy Journal

SPECIAL SECTION: NEAR-TERM PROBLEMS IN MEETING WORLD FOOD DEMANDS AT REGIONAL LEVELS

Smallholder farmers' climate change adaptation practices contribute to crop production efficiency in southern Ethiopia

Dessalegn Anshiso Sedebo[1] | Gu-Cheng Li[1] | Kidane Assefa Abebe[2] | Bekele Gebisa Etea[2] | John Kojo Ahiakpa[3] | N'Banan Ouattara[1] | Ambaliou Olounlade[1] | Stephen Frimpong[4]

[1] College of Economics and Management, Huazhong Agricultural Univ., Wuhan 430070, P.R. China

[2] College of Business and Economics, Ambo Univ., Ambo, Ethiopia

[3] Research Desk Consulting Limited, Proton Street, Kwabenya-Accra, Ghana WY 2918, Ghana

[4] Division of Applied Social Sciences, Univ. of Missouri, Columbia 65201, USA

Correspondence
Gu-Cheng Li, College of Economics and Management, Huazhong Agricultural Univ., Wuhan, 430070, P.R. China
Email: lgcabc@mail.hzau.edu.cn

Assigned to Associate Editor Thandiwe Nleya.

Abstract

Climate-smart practices that have added benefits of improving agricultural productivity are an imperative for improving smallholder farming. However, there are few insights into how smallholder climate-smart adaptation practices influence their technical (in)efficiency. Thus, the objective of this study was to evaluate the impact of smallholders' climate-smart adaptation practices on their crop production technical efficiency (TE) in the Lemo district of southern Ethiopia. We used focus group discussion, experts' consultations and household survey to collect data from 600 smallholder crop producers across six rural kebeles. We computed smallholder farmers' climate change adaptation indices based on experts' consultations and estimated the TE of the smallholder farmers using Stochastic Frontier Analysis. The smallholder farmers in the Lemo district have adopted climate-smart agricultural practices such as terracing, crop diversification, improved soil amendment practices, varying planting or harvesting schedules, and crop rotation. The smallholder farm households practicing more adaptation strategies on a larger scale were more technically efficient than their counterparts with their TE averaging 11.31, 8.62, and 6.71% for major crops, wheat (*Triticum aestivum* L.), and teff [*Eragrostis tef*) (Zucc.) Trotter] production, respectively. Our model also revealed that adaptation to climate change has a positive and significant contribution to the technical efficiency of major crops, wheat, and teff production. Other key determinants of TE are farming experience, education, access to extension services, livestock holdings, and farm household income. Overall, our study suggests a policy shift to promote smallholder farmers adaptation to climate change using climate-smart practices for an effective response to climate change impact while enhancing TE.

Abbreviations: AAI, activity-based adaptation index; CD, Cobb–Douglas; LR, log-likelihood ratio; MLE, maximum likelihood estimate; SFA, stochastic frontier analysis; TE, technical efficiency.

1 | INTRODUCTION

Climate change can have both direct and indirect impacts on the general well-being of smallholders as smallholder farming communities primarily depend on climate-controlled agriculture and forest resources for their livelihoods. For instance, a marginal increase in temperature can reduce yields in agriculture at lower latitudes, and potential yield decline has been recorded in many parts of the world (IPCC, 2007). Also, changes in temperature and precipitation generally cause changes in land and water resources, such as drought, high evapotranspiration, high post-production losses, and high incidences of diseases and pests, which subsequently affect agricultural productivity (World Bank, 2003). The agricultural sector, in this case, crop production, represents an important economic segment for assessing climate change impacts. This is because agriculture encompasses ecosystem and society, and it is extremely influenced by alteration in environmental conditions (Oelesen & Bindi, 2002; IPCC, 2012).

Lobell and Field (2007) established that food prices, food security, and land use are negatively hurt by climate change. The level of climate-smart adaptation at the farm level comprises smallholder farmers' investment decisions and policy choices as the main determinants of the extremeness of climate change impact (Kahil et al., 2015). Yet not many smallholder farmers in Ethiopia integrate climate-smart adaptation practices in their farming activities. Only few smallholder farmers in Ethiopia uses climate adaptation and mitigation practices as independent options to respond to climate change.

Given the low level of investment in the industrial sector, mitigation may not be suitable for Ethiopia as it may deter growth registered in the preceding years. Instead, adaptation using different improved varieties of crops, planting of trees, soil conservation, and adjusting planting schedule may be the ideal autonomous strategy for smallholders to cope with climate change impacts (Temesgen et al., 2008). Thus, adaptation strategies must be tailored to the uniqueness and peculiarities of countries.

Asrat and Simane (2018) indicated that, to implement relevant policy, it is required to understand location-specific scenarios, context, and forces that provoke adaptation. Autonomous adaptation is done at the farm-level; which is generally insufficient and needs the involvement of various stakeholders (Maddison, 2007; Semenza et al., 2008; Simane et al., 2016). Additionally, national and international adaptation programs need an in-depth analysis of site-specific scenarios and how climate-smart practices at the farm-level influence smallholder technical efficiency (TE) (Bryan et al., 2009).

Empirically, Below et al. (2012) modelled an activity-based adaptation index (AAI) and established a connection between and among socio-economic factors and smallholder farmers' adaptation practices. This study was limited by the creation of an adaptation index that only accounted for the rate of adaptation practices adopted, without assessing the scale of actual performance of those practices. Although, there is varied evidence that, good adaptation practices increase agricultural productivity; smallholder farmers' climate change adaptation practices and their associations with farm-level crop production efficiency, especially in Ethiopia is an evolving area of research (Yesuf et al., 2008; Di Falco et al., 2011).

Core Ideas

- An activity-based adaptation index for climate change was measured.
- There was positive correlation between climate change adaptation practices and crop production efficiency.
- Smallholder climate-smart adaptation practices have significant effect on technical efficiency.
- Farmers using climate-smart practices at a larger scale are more technically efficient.

In line with this, Khanal et al. (2018) reported that there is little knowledge about whether smallholder farmers' adaptation practices in developing countries enhance the efficiency of farm production. This necessitates location-specific studies on the linkage of adaptation practices with crop production efficiency. Again, Adego et al. (2019) emphasized the need for context-specific studies, as previous studies were limited to the impacts of adaptation interventions on smallholder agriculture. We bridge the knowledge gap on the effects of smallholder climate-smart adaptation practices on the effects of farmers TE in the southern part of Ethiopia. Thus, the objective of this study was to assess the impact of climate-smart adaptation strategies on crop production TE and explore key determinants of TE of smallholder crop production in the study area. Our findings serve as a means for Ethiopian agricultural policy makers to advocate for widespread adoption of climate-smart agricultural practices.

2 | MATERIALS AND METHODS

2.1 | The study area

Lemo district is one of the districts in the Hadiya zone of southern Ethiopia. The Lemo district has 33 rural kebele*s* (i.e., is the lowest administrative unit in Ethiopia) and three municipalities. There are 178,535 inhabitants in the district. Geographically, the district is located between 7°22′ and 7°45′ N latitude and 37°40′ and 38° E longitude and covers an area of 34,986 ha, of which 78.23% is under annual and perennial crop production. The average yearly temperature ranges from 15 to 22 ˚C and rainfall is between 700 to 1,260 mm (LDARDO, 2019). The rainfall distribution is intensive during *kiremit* (June–September); relatively stable in *Belg* (March–May) and light for the rest of the year. The district has a frequently varying climatic condition. For instance, the spring months are becoming drier to the extent of no variation with the winter season. Lemo is generally considered as a highland zone, even though there are minor differences among the kebeles, and thus are classified as dry, wet, and moderate depending on highland characteristics. Following this, we selected two kebeles from the three categories for inclusiveness and representativeness of the study. However, our analyses were not based on these classifications since the difference between kebeles were not significant as per the discussion held with the Lemo district agricultural and natural resource experts prior to our study. Cereals are the most cultivated crops in the area which accounts for about 60% of all crop production. Wheat (*Triticum aestivum* L.) is the most dominant cash crop produced in the district followed by teff *(Eragrostis tef* (Zucc.) Trotter; a small-sized cereal grain, indigenous to Ethiopia), barley (*Hordeum vulgare* L.), maize (*Zea mays* L.), and sorghum [*Sorghum bicolor* (L.) Moench]. Wheat, teff, barley, maize, and sorghum were considered as major crops in this study.

2.2 | Sampling technique and sample size

We used a three-stage sampling method in this study. The Lemo district was selected due to its potential in cereal crops production both in Hadiya and southern Ethiopia. We randomly selected six rural kebeles from the 33 rural kebeles in the district. A total of 600 rural crop-producing households were interviewed and from the interviewed respondents, nine were excluded from the analysis as there were missing data in major variables. Representative sample households were proportionally selected from each kebele. The selected sample size accounts for approximately 16% of the total crop-producing households who are residents in the kebeles as recommended by Kumar (2006).

2.3 | Data collection

We collected primary data from structured household survey, focus group discussions (FGDs), experts'/stakeholders' consultations, and field observations. The structured survey questionnaire focused on input–output data of crop production, socio-economic factors, climate change perception and adaptation practices used by the smallholder farmers (Table 1), institutional factors, and other relevant information based on existing literature (Amarender, Reddy & Bantilan, 2012; Chen et al., 2009; Duvivier, 2013; Khanal et al., 2018). To identify smallholder adaptation practices and pretest the survey instrument, we undertook a preliminary assessment. The questionnaires were modified based on feedbacks from the pre-testing. Six experienced enumerators who have prior experience, good knowledge of the study areas and language were selected and trained on the survey questionnaires. This was done in collaboration with the Lemo district agricultural and natural resource officers. Close supervision was provided at the field level during data collection by the researchers and the Lemo district agricultural and natural resource officers. We collected data from December 2019 to February 2020. Data were analyzed using both descriptive statistics and econometric model in Stata statistical software (ver. 15) (StataCorp., 2017).

2.4 | Measuring farm-level adaptation to climate change

We computed activity-based adaptation index (AAI) of smallholder farmers adaptation practices to climate change (see similar approaches in Below et al. (2012) and Khanal et al. (2018). First, we explored farmer adaptation practices which are presently practised by farmers in the district. This was done through a review of relevant literature, expert's consultations, field observations and FGDs with smallholder farmers in each sampled kebele. We excluded practices that have no relation with climate change impacts. Then, we organized 24 local experts to assign weight to each selected adaptation practice identified in the field studies based on the proven ability of the practice to minimize climate change effects. The participants were senior agricultural officers from the Hadiya zone and Lemo district agricultural and natural resource offices, Wachemo University, Agri-farm service (NGO), and model farmers from the six kebeles. In the study district, 18 climate-smart adaptation practices were identified, and weights were assigned to them. The rating scale ranged from 0 to 3, where 0, 1, 2, and 3 means the practice has no, low, moderate, and high effect to mitigate climate change impacts, respectively. For instance, among the 24 experts, none rated crop diversification as having a zero effect to mitigate climate change impact, one of the experts rated crop diversification as having a low ability to mitigate climate change impact, while 13 and 10 experts rated crop diversification as moderately and highly effective in mitigating climate change impacts (Table 1). We summed the scores from each expert for each of the 18 practices to obtain the total weight (Equation 1) (Below et al., 2012).

$$\mathrm{AAI}_j = W_1 \ V_{1j} \ + \cdots \cdots .. W_n V_{nj} \tag{1}$$

TABLE 1 Smallholder farmers climate-smart adaptation practices and their estimated score by experts/stakeholders

S/N	Adaptation strategies/practices	No. of experts assigning weights to specific practices[†] No impact (0)[a]	Low impact (1)[a]	Moderate impact (2)[a]	High impact (3)[a]	Total weight	Score percentage ($AAIP_j$)
							%
1	Crop diversification	0	1	13	10	57	79.17
2	Use of drought tolerant varieties	0	2	12	10	56	77.78
3	Use of short duration varieties	0	4	12	8	52	72.22
4	Use of disease/pest resistant varieties	4	6	8	6	40	55.56
5	Use of less water intensive varieties	5	5	11	3	36	50.00
6	Practicing crop rotation	0	4	7	13	57	79.17
7	Intercropping/mixed cropping	2	4	10	8	48	66.67
8	Change planting date and harvesting date	1	3	9	11	54	75.00
9	Preparation of check dam	1	5	9	9	50	69.44
10	Preparation of water ways	1	3	11	9	52	72.22
11	Reducing tillage	4	5	10	5	40	55.56
12	Agroforestry	0	5	9	10	53	73.61
13	Soil conservation technique	0	1	10	13	60	83.33
14	Use of compost and farm yard manure	0	3	9	12	57	79.17
15	Use of improved chemical fertilizer	3	5	6	10	47	65.27
16	Shift to livestock, instead of crops	7	9	5	3	28	38.89
17	Shift to off-farm/non-farm work	7	6	6	5	33	45.83
18	Closely follow weather forecasts	2	4	8	10	50	69.44

Note. Score % = $[\frac{\sum \text{Maxk} \times n}{\text{MaxMark} \times n}] \times 100, n = 24, \text{MaxMark} = 3$. S/N, serial number; AAIP, activity-based adaptation index percentage.
[a] Numbers in parentheses refer to numbers of experts assigned the respective weight to each practice.

where activity-based adaptation index $(\text{AAI})_j$ is the adaptation index of respondents j; W_1 is the score of weights for adaptation practice 1; V_{1j} is the jth respondent value for practice 1 (1 if the jth respondent adopted practice 1 and 0 if not).

After summation of the indices, we converted the indices into a percentage using the formula by Lisandro et al. (2017). This was formulated as the sum of all the practices on a given farm multiplied by the weight assigned by experts (W_{ji}), divided by the sum of all weights (W_i) for jth smallholder farmers (i.e., 1–591) and jth 1–18 practices stated as:

$$\text{AAIP}_j = \left[\frac{\sum_{i=1}^{18} W_{ji}}{\sum_{i=1}^{18} W_i}\right] \times 100 \tag{2}$$

Hence, activity-based adaptation index percentage $(\text{AAIP})_j$ value falls between 0 and 100%, and 100% suggests that the practice yields the uppermost result from experts.

2.5 | Technical efficiency estimation

We used the Stochastic Frontier Analysis (SFA) to measure smallholder crop production efficiency which is subject to different environmental influences including meteorological conditions that is usually not controlled by smallholder farmers. The linear stochastic frontier model is conditioned on x and z, y, and distributed as N (x' β, σ^2). This is in line with the standard regression model, which has an explicit error term υ;

$$y = x' \beta + \upsilon \tag{3}$$

where υ is $N(0, \sigma_\upsilon^2)$ and is independent of x and z (Wang & Schmidt, 2002). Thus, the stochastic frontier model can be written as:

$$\ln y_i = \ln f\left(x_i; \beta\right) + (\upsilon_i - u_i)\ i \ldots .\ N \tag{4}$$

where y_i is the production volume of farm i in Log form; x_i is the amount of inputs used in production by ith farmer in Log form; β is the unknown parameters to be estimated; υ_i are random variables that are assumed to be identically and independently distributed, $N(0, \sigma_\upsilon^2)$ are two-sided random errors, independent of u_i, representing random shocks, such as exogenous factors, measurement errors, omitted explanatory variables, and statistical noise; and u_i are random variables (non-negative), related to inefficiency in production, assumed to be independently distributed as truncations at 0 of the N $(z_{i,}\sigma_u^2)$ distribution;

$$U = \delta_0 + \sum_{i=1}^{i} z_{ji} \tag{5}$$

$u_i$denotes technical inefficiency of ith households, z_{ji} is the vector of variables of climate change adaptation practice and socio-economic factors (hypothesized efficiency of changing variables), and δ denotes the vector of parameters to be estimated.

Battese and Coelli (1995) included farm-specific attributes in a "direct" or "single-stage" efficiency model. We estimated the production frontier and inefficiency explanatory factors in a single step using the "one-stage" method as shown in Equation 6.

$$\ln y_i = \ln f\left(x_i\ z_i;\beta\right) + v_i - u_i \tag{6}$$

At the farm level, the widely applied production efficiency functional forms are Cobb–Douglas (CD) and Transcendental Logarithmic (translog) (Thiam et al., 2001). The translog form has the advantage of flexibility considering few assumptions, but this was criticized for the appropriateness of small data size. Conversely, the CD form has advantages of simplicity in measuring returns to scale of inputs (Neumann et al., 2010). First, CD production function model was specified and its suitability was tested over the translog model. As a result, we found that CD functional form is a better fit for our data. Thus, according to Coelli (1996), the CD functional form and the translog functional forms were expressed in Equations (7) and (8).

$$\ln Y_i = \beta_0 + \sum B_i \ln x_{ij} + \left(v_i - u_i\right) \tag{7}$$

$$\ln Y_i = \beta_0 + \sum_{i=1}^{n} \beta_i \ln x_{ij} + \sum\sum_{i=1}^{n} \beta_{jk} \ln x_{ij} \ln x_{ik} + v_i - u_i \tag{8}$$

where ln Y_i represents farm output in kg ha^{-1} of ith farmer, ln x_i denotes the number of input quantities applied in an ith farm in log form, β is the vector of unknown parameters to be estimated, v_i andu_i represents random shocks and inefficiency factors as defined in Equation 4.

The ratio of the observed output for the ith farm, relative to the potential output, defined by the frontier function; given the input vector x_i defines the TE of the ith farm. Thus, the measures of TE relative to the production frontier was defined as:

TABLE 2 Generalized likelihood ratio test of hypotheses and model specifications

Null hypothesis	LR	χ^2 value	Decision
Ho: $\delta_0 = = \delta_2 = \ldots = \delta_{21}$	20.32	32.67**	accepted
Ho: $\gamma = 0$	236.41	3.84 **	rejected
Ho: $\beta_0=\beta_1=\beta_2 = \ldots = \beta_{11} = 0$	100.04	18.31**	rejected

Note. LR, log-likelihood ratio.
**Significant at .05.

$$\mathrm{TE}_i = \frac{y_i}{\exp\ (x'_i\ \beta + v_i)} = \frac{\exp\ (x'_i\ \beta + v_i - u_i)}{\exp\ (x'_i\ \beta + v_i\ )} = exp\ \left(-u_i\right) \tag{9}$$

where y_i =exp $(x'_i\ \beta + v_i - u_i)$ is the stochastic frontier model for ith household, TE$_i$ is the range of values between 0 and 1. The exp ($-u_i$) is a log form dependent variable defined from the efficiency of production of farm i to the corresponding inputs level.

2.6 | Test for model specifications

The primary test was based on the hypothesis of the functional form of adequacy (CD against Translog function). To select the best repressing production function, we used the generalized log-likelihood ratio test (LR) as follows:

$$\lambda = -2\ \log\left[\frac{L\,(Ho\,)}{H_1}\right] = -2\log\left[L\,(Ho)\right] - \log\left[L\left(H_1\right)\right]$$

where log[$L(Ho)$] is the null hypothesis, Ho (CD function) LR value, and log[$L(H_1)$] is the alternative hypothesis, H_1 (translog function) LR value. The computed LR ratio was 20.32 while the critical LR of 21 degrees of freedom at .05 level of significance wasχc^2 .05, 21, which equals to 32.67 (Table 2). Based on these values, the null hypothesis was accepted. Thus, for the data at hand, the CD function was more reliable.

Also, the appropriateness of the SFA over the traditional production function was validated by testing whether there exists technical inefficiency in the production process or not. In this test, the null hypothesis is given as : $\gamma = \delta_1 = \delta_2 = \delta_3 = \cdots \delta_6 = 0$. The calculated LR test statistics was 236.41, exceeding the criticalχc^2 (5%, 1) value of 3.84 at .05 level of significance (Table 2), implying rejection of the null hypothesis. This confirms that there was significant inefficiency in the production process and SFA is appropriate for the data.

TABLE 3 Socio-demographic characteristics of smallholder farmers in the study area

Variables[a]	Major agricultural crops (N = 591) Mean	SD	Wheat (N = 537) Mean	SD	Teff (N = 305) Mean	SD
Output, kg ha^{-1}	937.81	880.81	848.92	766.16	311.15	286.58
Land, ha	0.58	0.70	0.46	0.69	0.29	0.21
Labor, n	5.99	4.261	4.07	2.23	4.2	1.96
Oxen, n	1.80	0.601	1.80	0.62	1.82	0.61
Seed, kg ha^{-1}	106.45	85.40	89.87	80.68	24.83	18.79
Fertilizer, L ha^{-1}	118.41	102.17	92.53	72.32	62.22	66.49
Chemical, L ha^{-1}	7.74	7.87	6.08	6.15	4.04	3.69
Adaptation index, %	44.14	27.51	48.34	24.85	44.48	20.81
Gender (m/f)	0.85	0.35	0.84	0.37	0.90	0.30
Age, yr	49.13	11.80	49.81	11.82	50.61	11.88
Farm experience, yr	23.40	10.27	23.68	10.42	25.10	10.13
Educational level (sch)	4.38	3.24	4.34	3.20	4.52	3.32
Plot number, n	1.68	0.80	1.30	0.59	1.06	0.35
Extension service, d/mo	2.60	2.51	2.72	2.55	2.97	2.77
Distance to farm, m	16.36	17.31	14.35	15.63	12.40	8.373
TLU	3.93	2.21	4.03	2.16	4.64	2.16
Access to credits (yes/no)	0.56	0.49	0.57	0.49	0.58	0.49
Farm income (US$)	190.95	308.09	198.03	315.98	238.17	340.86

Note. TLU, tropical livestock unit.
[a]N = sample number. Output was measured as kg ha^{-1}; land was measured in hectares (ha); labor and oxen were measured as number of persons and oxen power employed (n); seeds and fertilizers were measured as kg ha^{-1}; chemical was measured as L ha^{-1}; adaptation index was measured as a percentage (%); gender was rated as male = 1; female = 0 (m/f); Age and farming experience were in years (yr); educational level was year of schooling; plot number was parcel of land as number (n), extension services was number of visit days per month (d/mo); distance to farm was measured as minutes' walk (mins); livestock stock was measured as tropical livestock unit; access to credit was dummy as yes = 1; no = 0 and farm income was estimated in U.S. dollars.

The third hypothesis test was about whether farm-level technical inefficiencies was affected by the socio-economic variables included in the inefficiency model. The estimated LR value of 100.04 was greater than the critical value of 19.68 at 11 degrees of freedom. The result shows that the null hypothesis (*Ho*) explanatory variables are simultaneously equal to zero and ought to be rejected at a .05 significance level. Therefore, there is at least one variable that explains the difference in the inefficiency among the smallholder farm households.

3 | RESULTS AND DISCUSSION

3.1 | Outputs, inputs, and inefficiency determinants

The mean output in kilograms for the 2019 production season were 937.81, 848.92, and 311.15 for major agricultural crops, wheat, and teff, respectively (Table 3). The average farm sizes of the smallholder major crop, wheat and teff producers were 0.58, 0.46, and 0.29 ha, respectively. The mean number of household members providing farm labor were 5.99, 4.07, and 4.2 for major crops, wheat, and teff, respectively. Also, the mean number of oxen used for all crop production was approximately 1.80. On average, seed and chemical fertilizer use declined from major crops to teff production (Table 3). On average, chemicals applied for weed, insects, and pests' control were 7.74, 6.08, and 4.04 L ha^{-1} for major crops, wheat, and teff farms, respectively. Moreover, average adaptation indices for smallholder major crops, wheat, and teff-producing farm households are 44.14, 48.34, and 44.48%, respectively. The majority (85%) of households were male-headed and the remaining 15% were female-headed for the major crops. Similarly, wheat and teff productions are dominated by males. The household head has an average age of 49.13 yr, a farming experience of 23.40 and 4.38 yr of education for major crop producers. Nearly similar values of these variables were observed for wheat and teff farming households. On average, respondents had a plot number of 1.68 farm fields, contact frequency with extension agents of 2.60 d per month and 16.36 min "walking distance" to farms. Also, the smallholder farming households have an average livestock stock number of 3.90 in tropical livestock unit (TLU) and

TABLE 4 Climate-smart practices frequently adopted by smallholder farmers in the study area in percentage

Adaptation practices	Major crop farmers (N = 591)[a,b]	Wheat farmers (N = 537)[b]	Teff farmers (N = 305)[b]
No adaptation practice	27.36	32.43	37.92
Crop diversification	56.14	40.92	35.08
Using drought tolerant varieties	38.05	37.21	19.50
Using short duration varieties	35.85	20.70	13.60
Using disease/pest resistant varieties	29.91	30.55	11.14
Using less water intensive varieties	5.38	8.56	2.88
Crop rotation	47.69	40.33	45.24
Intercropping/mixed cropping	14.53	2.45	2.35
Change planting date/harvesting date	51.76	42.52	41.56
Preparation of check dams	10.64	18.95	22.95
Preparation of water ways	11.99	26.20	10.81
Agroforestry	19.59	8.34	2.11
Reducing tillage	12.33	19.89	17.34
Soil conservation practices	58.57	46.35	45.57
Use of compost and farm yard manure	41.43	21.30	21.47
Using improved chemical fertilizer	52.48	45.42	45.90
Shift to livestock, instead of crops	6.92	3.68	4.56
Shift to off-farm/non-farm activity	21.31	13.56	12.00
Closely follow weather forecasts	28.91	24.56	14.56

[a] N is the sample number.
[b] Multiple crop producers.

US$190.95 annual income from the main crops. About 56% of main crops, 57% of wheat, and 58% of teff farmers had access to credit (Table 3).

3.2 | Climate-smart adaptation practices by smallholder farmers in the study area

Smallholder farm households in the study area use various climate-smart practices to combat the effects of climate change on their farms and livelihoods. The summary statistics show that smallholder farm households (major crops = 72.64%, wheat = 67.57%, and teff = 62.08%) used at least one practice in response to climate change on their farms (Table 4). The major practices that were adopted by the major crop growing smallholder farmers were terracing (soil conservation technique) (58.57%), followed by crop diversification (56.14%), improved chemical fertilizer use (52.48%), and varying planting or harvesting dates (51.76%). Wheat-growing smallholder farmers adopted practices like soil and water conservation techniques (46.35%), increased chemical fertilizer use (45.42%), adjusting planting or harvesting dates based on changing rainfall patterns (42.52%), crops diversification (40.92%), and rotation (40.33%), respectively. Similarly, teff growers practised increased chemical fertilizer use (45.90%), soil conservation (45.57%), and adjusting crop planting and harvesting dates (41.56%) as adaptation strategies to mitigate the long-term effect of climate change.

3.3 | Climate change adaptation practices and crop production inefficiency

The maximum likelihood estimates of CD production function results (Table 5) indicated that all input variables had a positive and significant effect on major crop production, thus, an increase in one of the inputs will enhance production. Likewise, in wheat production, except labor, all other inputs were found to have a significant and positive effect on production in the Lemo district. Conversely, only the number of oxen was not a significant variable in explaining the variation in output among smallholder farmers in teff production. Moreover, the production return to scale for major crops, wheat, and teff were 0.97, 0.92 and 0.82, respectively. This implies that the production is in decreasing returns to scale. Thus, for the smallholder farming households, an increase in all inputs by a certain percentage would trigger an increase in output by less than that percentage.

The inefficiency model was simultaneously estimated with the CD frontier model using a truncated normal distribution (see inefficiency model variables in Table 5). Climate change adaptation practices are the most primary variables for this

TABLE 5 The maximum likelihood estimates of the stochastic frontier analysis of the Cobb–Douglas production function

	Major crops			Wheat		Teff	
Frontier variables	**Parameters**	**Coefficients**	**SE**	**Coefficients**	**SE**	**Coefficients**	**SE**
Constant	(δ_0)	5.8406***	0.2814	5.4740***	0.2678	5.3930***	0.2466
ln Land	(δ_1)	0.4941 ***	0.0522	0.2331***	0.0558	0.3115***	0.0557
ln Labor	(δ_2)	0.1495**	0.0494	0.0772	0.0583	0.1144**	0.0648
ln Oxen	(δ_3)	0.0738 ***	0.0799	0.2246 ***	0.0839	0.0735	0.0886
ln Seed	(δ_4)	0.2441**	0.0771	0.1032**	0.0679	0.1629 ***	0.0445
ln Fertilizer	(δ_5)	0.0398***	0.0821	0.1474**	0.0810	0.0678**	0.0381
ln Chemical	(δ_6)	0.0519***	0.0314	0.1297***	0.0421	0.0832**	0.0496
Inefficiency model variables							
Constant	β_0	4.629 ***	0.8007	3.4936***	1.045	0.5921	0.3786
Adaptation index	β_1	–0.0022***	0.0005	–0.0078***	0.0066	–0.0083***	0.0038
Age	β_2	–0.0212	0.0091	–0.0387***	0.0142	–0.0066	0.0047
Farm experience	β_3	–0. 0524***	0.0042	–0.0253**	0.0124	–0.0242**	0.0321
Education	β_4	–0.2112***	0.0456	–0.1090***	0.0419	–0.0179***	0.0023
Land size	β_5	–0.5941	0.2588	–0.7396	0.5638	–0.1501	0.1150
Extension service	β_6	–0.9699***	0.3338	–0.1612**	0.0788	–0.4203***	0.1015
Distance to farm	β_7	0.0072	0.0045	0.0131***	0.0046	0.0065	0.0058
TLU	β_8	–0.4110***	0.0858	–0.1110	0.0779	–0.1357***	0.0393
Access to credit	β_9	–0.0493	0.1962	–0.1932	0.2071	–0.0812	0.1076
Gender	β_{10}	–0.2122	0.2603	–0.3245	0.2504	–0.2952	0.1362
Farm income	β_{11}	–0.0034**	0.0002	–0.0003***	0.0008	–0.0039**	0.0005
Sigma_ u	δ_u	0.8305***	0.0831	0.6453***	0.0891	0.4579***	0.0297
Sigma _ v	δ_v	0.4022***	0.0215	0.5732***	0.0259	0.3450***	0.0765
Lambda	λ	1.3566 ***	0.0925	1.1257***	0.0980	0.7535***	0.0954
Return to scale		0.9675		0.9152		0.8133	
TE		0.6995		0. 6573		0.7510	
Log-likelihood function		–571.7924		–430.4371		–235.4017	

Note. TE, technical efficiency; TLU, tropical livestock unit.
**Significance at .05. ***Significance at .01.

study. The results clearly showed that the adaptation index for climate change has a negative and significant effect on the inefficiency of major crops, wheat, and teff productions. This indicates that adaptation of climate-smart practices can contribute to smallholder farm efficiency. It is cogent that, adjusting farm activities with weather change can help farmers to enhance TE as smallholder agriculture is partly a weather-dependent business. Similarly, Khanal et al. (2018) and Lisandro et al. (2017) reported a positive impact of adaptation practices on agricultural production efficiency in Nepal and Central Chile which are consistent with the findings of our study.

As far as other determinants of production efficiency were concerned, age had a negative and significant impact on wheat production inefficiency, but not significant in the case of major crops and teff production. Previous studies indicate that the association of farmers' age and TE differs based on geographic location. For example, Lisandro et al. (2017) and Tan et al. (2010) found a positive association between age and TE. Contrary, a negative and significant association was reported by Jaime and Salazar (2011) and Mariano et al. (2011) among Chilean farmers and Philippines rice (*Oryza sativa* L.) producers, respectively. Thus, the negative relationship between age and TE shows that as farmers age increases, their crop production inefficiency declines. The possible justification for this is that older farmers accumulate more knowledge and experiences in their farming activities and act accordingly to enhance productivity as they age on.

Undoubtedly, for all production systems, the relationship between farming experience and technical inefficiency was negative and significant. This emphasizes that, as farming experiences of smallholder farm households increase, their crop production efficiency also increases. This may be ascribed to the fact that smallholder farmers with better experience in farming can manage agronomic activities and easily adopt new practices. This, ultimately increase their TE level in crop production, thus corroborating Khanal et al. (2018) and Chen, Huffman, and Rozelle (2009) who reported a positive relationship between farming experience and TE.

Again, we found education level has a significant and negative correlation with major crops, wheat, and teff production inefficiency. This implies that educated farmers were more efficient in their farm activities than their uneducated counterparts. Jaime and Salazar (2011) demonstrated that education improves access to information, facilitates learning and eases adoption of new innovations, practices, and promotes forward-looking attitudes among smallholder farmers. Liu and Zhuang (2000), and Solís et al. (2009) reported similar findings which corroborate the results of this study. Our observation from the field indicated educated farmers were well-informed about practical innovations and good agronomic practices especially for their line of business and climate.

The results revealed that access to extension services and frequency of contact by smallholder farmers with extension workers influence the technical inefficiency of smallholder farms significantly and negatively for all crop producers. Specifically, the more frequent crop producers interact with extension service workers (referred to as development agents in Ethiopia), the better their TE. Recent findings by Abebaw et al. (2020), and Abate et al. (2019) in the northern parts of Ethiopia and Abdulai et al. (2018) in the Sagnarigu district of Ghana are consistent with our findings. Again, distance to farm had a positive relationship with the technical inefficiency of major crops and teff production, but significant only for wheat crop production. This suggests that smallholder households living closer to their farms are more efficient than those located far from their farms. This could be justified as the location of farms away from the farmers' place of residence incurs an additional cost in travel for smallholders, limiting adequate farm management and supervision. Thus, this may partly account for the low TE; which is in consonance with reports by Dessie et al. (2020) and Fantu et al. (2015) who reported that distance to farm in smallholder agriculture is a key limiting factor to TE.

The number of livestock is considered as a proxy indicator of household wealth status in rural Ethiopia. From our analysis, livestock holding has a negative and significant effect on production inefficiency. Abebaw, Mesay, and Shewaye (2020) stated that livestock ownership may positively affect the TE of smallholder farm households in two ways in Ethiopia. First, proceeds from the sale of livestock are used to finance necessary farm inputs (including chemical fertilizers and pesticides). Secondly, households with a greater number of livestock holding may easily supply oxen draught power for plowing and threshing as a source of labor, and organic fertilizer mainly from their excreta. This agrees with a report by Tadele et al. (2018) in Ethiopia. The study revealed that income from farm activities significantly and negatively influences major crops, wheat, and teff production inefficiency. This suggests that farmers who generate more income from crop production are technically efficient. Hailemaraim (2015) stressed the potential ripple effect of plowing back earnings into farming operations by smallholder farmers to increase TE.

TABLE 6 Summary of mean efficiency score for the three crop groups under the study

Types of crops	No. of observation	Mean TE	SD	Min.	Max.
Major crops	591	0.6995	0.2085	0.0886	0.9792
Wheat	537	0.7510	0.1887	0.0926	0.9818
Teff	305	0. 6573	0. 1827	0.1646	0.9653

Note. TE, technical efficiency.

3.4 | Technical efficiency score and adaptation level

The mean TEs for major crops, wheat, and teff productions were 69.95, 75.10, and 65.73%, respectively (Table 6). The relatively lower value (65.73%) of TE score was observed for teff production, but with a better minimum value. Additionally, the results showed that, there is a wide disparity among households in all production systems in their level of TE. This also indicates that there is more room for improving the existing level of crop production amid climate variability. Furthermore, the mean level of TE interpreted as the level output of the smallholder farms could be increased, on average by 30.35% for major crops, 24.9% for wheat, and 34.73% for teff if appropriate climate-smart practices are executed to improve the efficiency in their productions. Thus, there is an opportunity to increase these values by using the resources at their disposal without introducing new inputs. Moreover, the varied levels of TE are common in agricultural production. This might be justified as different crops might respond differently to climate change impacts. Besides, differences in soil fertility status of farmers' lands and extreme climate variability in the agro-ecology may contribute differently to climate change impact on different crops; and thus, culminating in the diverse efficiency levels of crop production in the study area. Wassie (2014) reported different efficiency levels for six major crops in Ethiopia.

We divided households into two categories following their adaptation indices and by using the median as cut off point (Table 7). Major crop farmers with a high climate-smart adaptation index were 11.3% more technically efficient than their counterparts with low adaptation index. Likewise, wheat and teff producers who had a higher adaptation index were more efficient than those with a lower level of adaptation by 8.62 and 6.71%, respectively. Overall, the findings implied wider adaptation level of the climate-smart practices by the

TABLE 7 Mean technical efficiency (TE) and standard deviations (SD) for farmers with low and high adaptation

Adaptation level in crop type	No. of observations	Mean TE	SD	*P* value
Major crops				
Low	280	0.6430	0.2049	
High	311	0.7561	0.2113	.0000
Wheat crop				
Low	150	0.7079	0.1897	
High	387	0.7941	0.1883	.0000
Teff crop				
Low	206	0.6383	0.1625	
High	99	0.6969	0.1890	.0003

smallholder farmers has a significant and positive contribution to farm households' TE.

4 | CONCLUSION

This study ascertained whether smallholder farmers' adaptations to climate change contribute to crop production efficiency. Stochastic frontier analysis using farmers adaptation indices was performed. The results of the production frontier analyses revealed that, all inputs, except labor and oxen power in wheat and teff productions were key determinants in the production of all crops; thus, an increase in one unit of inputs will augment production. The study established that adaptation to climate change impacts has an incremental contribution to the efficiency of smallholder crop production. Moreover, smallholder farmers' adaptation using more climate-smart practices on a larger scale could significantly increase TE of smallholder agriculture. Further, adaptation was found to be a significant variable in explaining TE discrepancies among smallholder farming households; demonstrating the contributions of climate-smart agricultural practices to smallholder farm productivity.

The mean TE indicates smallholder farming households in major crops, wheat, and teff productions were not technically efficient in the Lemo district; suggesting an opportunity to increase TE by using resources at their disposal without necessarily introducing new technologies. Additionally, efficiency improvements can be achieved by exposing smallholder farmers to more farming experience through farm visits and field demonstrations, and increasing educational opportunities. Likewise, farmers' TE can be further improved by extension workers frequently visiting smallholder farmers. Our study will be an addition to current AAIs for assessing climate change effects on smallholder agriculture. The study also provides empirical recommendations on the contribution of different adaptation strategies for smallholder crop production efficiency. We recommend that policy makers incorporate smallholder farmers' climate-smart practices into national adaptation programs for effective response to climate change impacts and to enhance TE of crop production. Equally, smallholder farmers' knowledge and skills of local climatic conditions and their traditional practices should be taken into account by involving them in planning adaptation strategies and actions.

ACKNOWLEDGMENT

The work was financially supported by the National Natural Sciences Foundation of China (NSFC No. 71873050). We are also grateful for Lemo district agricultural and natural resources offices for their support in the data collection.

AUTHOR CONTRIBUTIONS

Dessalegn Anshiso Sedebo: Conceptualization; Formal analysis; Investigation; Methodology; Software; Writing-original draft; Writing-review & editing. Gu-Cheng Li: Conceptualization; Funding acquisition; Project administration; Resources; Supervision. Kidane Assefa Abebe: Data curation; Methodology; Visualization; Writing-review & editing. Bekele Gebisa Etea: Data curation; Methodology; Visualization; Writing-review & editing. ; John Kojo Ahiakpa: Validation; Visualization; Writing-original draft; Writing-review & editing. N'Banan Ouattara: Data curation; Investigation; Visualization. Ambaliou Olounlade: Data curation; Investigation; Visualization. Stephen Frimpong: Methodology; Writing-review & editing.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest

ORCID

Dessalegn Anshiso Sedebo https://orcid.org/0000-0002-3122-0511

REFERENCES

Abate, T. M., Dessie, A. B., & Mekie, T. M. (2019). Technical efficiency of smallholder farmers in red pepper production in North Gondar zone Amhara regional state, Ethiopia. *Journal of Economic Structures*, *8*, 18. https://doi.org/10.1186/s40008-019-0150-6

Abdulai, S., Abraham, Z., & Samuel, A. D. (2018). Adoption of rice cultivation technologies and its effect on technical efficiency in Sagnarigu District of Ghana. *Cogent Food & Agriculture*, *4*, 1424296. https://doi.org/10.1080/23311932.2018.1424296

Abebaw, A., Mesay, Y., & Shewaye, A. (2020). Technical Efficiency of Lowland Rice Production in Northwest of Ethiopia. *Ethiopian Journal of Agricultural Science*, *30*, 99–111.

Adego, T., Simane, B., & Woldie, G. A. (2019). The impact of adaptation practices on crop productivity in northwest Ethiopia: An Endogenous Switching Estimation. *Development Studies Research*, *6*, 129–141. https://doi.org/10.1080/21665095.2019.1678186

Amarender Reddy, A., & Bantilan, M. C. S. (2012). Competitiveness and technical efficiency: Determinants in the groundnut oil sector of India. *Food Policy*, *37*, 255–263. https://doi.org/10.1016/j.foodpol.2012.02.004

Asrat, P., & Simane, B. (2018). Farmers' perception of climate change and adaptation strategies in the Dabus watershed, North-West Ethiopia. *Ecological Processes*, *7*, 7. https://doi.org/10.1186/s13717-018-0118-8

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, *20*, 325–332. https://doi.org/10.1007/BF01205442

Below, T. B., Mutabazi, K. D., Kirschke, D., Franke, C., Sieber, S., Siebert, R., & Tscherning, K. (2012). Can farmers' adaptation to climate change be explained by socio-economic household-level variables? *Global Environmental Change*, *22*, 223–235. https://doi.org/10.1016/j.gloenvcha.2011.11.012

Bryan, E., Deressa, T. T., Gbetibouo, G. A., & Ringler, C. (2009). Adaptation to climate change in Ethiopia and South Africa: Options and constraints. *Environmental Science Policy*, *12*, 413–426. https://doi.org/10.1016/j.envsci.2008.11.002

Chen, Z., Huffman, W. E., & Rozelle, S. (2009). Farm technology and technical efficiency: Evidence from four regions in China. *China Economic Review*, *20*, 153–161. https://doi.org/10.1016/j.chieco.2009.03.002

Coelli, T.(1996). *A guide to FRONTIER version 4.1: A computer program for stochastic frontier production and cost function estimation* (CEPA Working papers, No. 7/96). Department of Econometrics, University of New England. http://www.une.edu.au/econometrics/cepa.htm

Dessie, A. B., Abate, T. M., Adane, B. T., Tesfa, T., & Getu, S. (2020). Estimation of technical efficiency of black cumin (*Nigella sativa* L.) farming in northwest Ethiopia: A stochastic frontier approach. *Journal of Economic Structures*, *9*, 18. https://doi.org/10.1186/s40008-020-00198-1

Di Falco, S., Veronesi, M., & Yesuf, M. (2011). Does adaptation to climate change provide food security? A micro-perspective from Ethiopia. *American Journal of Agricultural Economics*, *93*, 829–846. https://doi.org/10.1093/ajae/aar006

Duvivier, C. (2013). Does urban proximity enhance technical efficiency? Evidence from Chinese agriculture. *Journal of Regional Science*, *53*, 923–943. https://doi.org/10.1111/jors.12054

Fantu, N., Bethlehem, k., & Alemayehu, S. (2015). *Cereal's productivity and its drivers: The case of Ethiopia* (IFPRI/ESSP II Working Paper 74). International Food Policy Research Institute.

Hailemaraim, L. (2015). *Technical efficiency in teff production: The case of Bereh District, Oromia National Regional State* (MSc thesis, Haramaya University).

Intergovernmental Panel on Climate Change (IPCC). (2007). *Climate change 2007: Impacts, adaptation and vulnerability (*Fourth Assessment Report). *Intergovernmental Panel on Climate Change*. Cambridge University Press.

Intergovernmental Panel on Climate Change (IPCC). (2012). *Managing the risk of extreme events and disasters to advance climate change adaptation*. Cambridge University Press.

Jaime, M., & Salazar, C. (2011). Participation in organizations, technical efficiency and territorial differences: A study of small wheat farmers in Chile. *Chile Journal of Agricultural Resource*, *71*, 104–113. https://doi.org/10.4067/S0718-58392011000100013

Kahil, M. T., Connor, J. D., & Albiac, J. (2015). Efficient water management policies for irrigation adaptation to climate change in Southern Europe. *Ecological Economics*, *120*, 226–233. https://doi.org/10.1016/j.ecolecon.2015.11.004

Khanal, U., Wilson, C., Lee, B., & Hoang, V.-N. (2018). Do climate change adaptation practices improve technical efficiency of smallholder farmers? Evidence from Nepal. *Climatic Change*, *147*, 507–521. https://doi.org/10.1007/s10584-018-2168-4

Kumar, S. Y. (2006). *Fundamental research methodology and statistics*. New Age International Private Limited.

Lemo District Agriculture & Rural Development Office (LDARDO). (2019). *Annual Socio-economic Report*. Hossana: The Lemo district.

Liu, Z., & Zhuang, J. (2000). Determinants of technical efficiency in post- collective Chinese agriculture: Evidence from farm-level data. *Journal of Comparative Economics*, *28*, 545–564. https://doi.org/10.1006/jcec.2000.1666

Lobell, D. B., & Field, C. B. (2007). Global scale climate-crop yield relations and the impacts of recent warming. *Environmental Resources Letter*, *2*, 1–7. https://doi.org/10.1088/1748-9326/2/1/014002

Maddison, D. (2007). *The perception of and adaptation to climate change in Africa* (Policy research working paper 4308). Development Research Group. The World Bank.

Mariano, M. J., Villano, R., & Fleming, E. (2011). Technical efficiency of rice farms in different agroclimatic zones in the Philipines: An application of a stochastic metafrontier model. *Asian Economic Journal*, *25*, 245–269. https://doi.org/10.1111/j.1467-8381.2011.02060.x

Neumann, K., Verburg, P. H., Stehfest, E., & Müller, C. (2010). The yield gap of global grain production: A spatial analysis. *Agricultural Systems*, *103*(5), 316–326. https://doi.org/10.1016/j.agsy.2010.02.004

Olesen, J. E., & Bindi, M. (2002). Consequences of climate change for European agricultural productivity, land use and policy. *European Journal Agronomy*, *16*, 239–262. https://doi.org/10.1016/S1161-0301(02)00004-7

Roco, L., Bravo-Ureta, B., Engler, A., & Jara-Rojas, R. (2017). The impact of climatic change adaptation on agricultural productivity in central Chile: A stochastic production frontier approach. *Sustainability*, *9*, 1648. https://doi.org/10.3390/su9091648

Semenza, J. C., Hall, D. E., Wilson, D. J., Bontempo, B. D., Sailor, D. J., & George, L. A. (2008). Public perception of climate change voluntary mitigation and barriers to behavior change. *American Journal of Preventive Medicine*, *35*, 479–487. https://doi.org/10.1016/j.amepre.2008.08.020

Simane, B., Zaitchik, B. F., & Foltz, J. D. (2016). Agro-ecosystem specific climate vulnerability analysis: Application of the livelihood vulnerability index to a tropical highland region. *Mitigation & Adaptation Strategies for Global Change*, *21*, 39–65. https://doi.org/10.1007/s11027-014-9568-1

Solís, D., Bravo-Ureta, B. E., & Quiroga, R. E. (2009). Technical efficiency among peasant farmers participating in natural resource management programs in Central America. *Journal of Agricultural Economics*, *60*, 202–219. https://doi.org/10.1111/j.1477-9552.2008.00173.x

StataCorp. (2017). *Stata statistical software: Release 15*. StataCorp LLC.

Tadele, M., Wudineh, G., Ali, C., Agajie, T., Tolessa, D., Solomon, A., & Tesfaye, S. (2018). Technical efficiency and yield gap of smallholder wheat producers in Ethiopia: A stochastic frontier analysis. *African Journal of Agricultural Research*, *13*, 1407–1418. https://doi.org/10.5897/AJAR2016.12050

Tan, S., Heerink, N., Kuyvenhoven, A., & Qu, F. (2010). Impact of land fragmentation on rice producers' technical efficiency in South-East China. NJAS Wagening. *Journal of Life Science*, *57*, 117–123. https://doi.org/10.1016/j.njas.2010.02.001

Temesgen, T. D., Rashid, M. H., & Claudia, R. (2008). *Measuring Ethiopian farmers vulnerability to climate change across regional states* (Environment and Production Technology Division Discussion Paper 00806). International Food Policy Research Institute (IFPRI).

Thiam, A., Bravo-Ureta, B. E., & Rivas, T. E. (2001). Technical efficiency in developing country agriculture: A metaanalysis. *Agricultura Economics*, *25*, 235–243. https://doi.org/10.1111/j.1574-0862.2001.tb00204.x

Wang, H.-J., & Schmidt, P. (2002). One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis*, *18*, 129–144. https://doi.org/10.1023/A:1016565719882

Wassie, S. B. (2014). Technical efficiency of major crops in Ethiopia: Stochastic frontier model. *Academia Journal of Agricultural Research*, *2*, 147–153. https://doi.org/10.15413/ajar.2014.0109

World Bank. (2003). *Africa rainfall and temperature evaluation system (ARTES)*. World Bank. Washington DC.

Yesuf, M., Di Falco, S., Deressa, T., Ringler, C. & Kohlin, G. (2008). The impact of climate change and adaptation on food production in low-income countries, evidence from the Nile Basin, Ethiopia (IFPRI Discussion Paper 00828). International Food Policy Research Institute.

How to cite this article: Sedebo D. A., Li G. -C., Abebe K. A., Etea B. G., Ahiakpa J. K., N' Ouattara B., Olounlade A., Frimpong S. Smallholder farmers' climate change adaptation practices contribute to crop production efficiency in southern Ethiopia. *Agronomy Journal*. 2021;*113:*4627–4638. https://doi.org/10.1002/agj2.20900