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Asmiro Abeje FIKADU
Department of Agricultural and Resource Economics, Graduate School of Bioresource and Bioenvironmental Sciences, Kyushu University

NOMURA, Hisako
Department of Agricultural and Resource Economics, Faculty of Agriculture, Kyushu University

Girma Gezimu GEBRE
Alexander von Humboldt Research Fellow at Leibniz-Centre for Agricultural Landscape Research (ZALF)

Payal SHAH
Okinawa Institute of Science and Technology Graduate University (OIST)

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The Impact of Adoption of Climate–smart Practices on Horticulture Yield: Lessons from Smallholder Horticulture Empowerment and Promotion Approach in Ethiopia

Asmiro Abeje FIKADU[1, 2], Hisako NOMURA[3]*, Girma Gezimu GEBRE[4] and Payal SHAH[5]

Laboratory of International Agricultural Development Studies, Department of Agricultural and Resource Economics, Faculty of Agriculture, Kyushu University, Fukuoka 819–0395, Japan

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Climate–smart practices in agriculture have been widely implemented to adapt to the adverse effects of climate change. Despite the growing literature on this topic, less attention has been given to evaluating their effects on horticulture yield. This study investigates the effects of adopting climate–smart horticulture (CSH) practices on horticultural yield in Jimma, Ethiopia, within the framework of the Smallholder Horticulture Empowerment and Promotion (SHEP) approach. Primary data were collected from 409 smallholder horticulture farmers in the Jimma zone, Ethiopia. Quantile regression and Inverse probability weighting regression adjustment (IPWRA) were used to estimate the heterogeneous effects of SHEP and adoption of CSH practices on aggregate weighted horticulture yield. The results show that adopting CSH practices increases yield by 43% among adopters. Moreover, through adopting disease–resistant varieties, the SHEP intervention positively affects yield across all quantiles. Therefore, the study underscores the need to scale up context–specific CSH practices alongside a market–oriented extension program. Strengthening farm demonstration programs and enhancing access to agricultural cooperatives can further support smallholder farmers in improving horticulture yield.

Key words: Adoption, Aggregate weight yield, Climate–smart horticulture practices, IPWRA, SHEP

INTRODUCTION

Smallholder farmers in developing countries continuously face challenges in enhancing agricultural productivity due to climate variability (Asfew & Bedemo, 2022), limited access to agricultural extension services (Leta *et al.*, 2017), and weak implementation of agricultural extension systems (Kitajima, 2024). Climate change significantly threatens global agricultural production, particularly affecting developing countries (Kalele *et al.*, 2021). The region's heavy reliance on rain–fed agriculture makes it especially vulnerable to climate variability. Although agriculture constitutes 40% of East Africa's GDP and sustains the livelihoods of 80% of the population in developing countries, shifts in temperature and precipitation patterns greatly diminish agricultural output (Musyimi, 2020), endangering the livelihoods of over 3.83 billion people who depend on the agri–food system (FAO, 2023). Climate change also encourages the increased presence and outbreaks of existing and new pests and diseases (Patrick *et al.*, 2020). Thus, developing countries will need an estimated $127 billion annually by 2030 and $295 billion annually by 2050 to adapt to the adverse effects of climate change (Intergovernmental Panel on Climate Change (IPCC), 2022).

Horticultural farming is one of the essential economic activities in East Africa (Nyasimi, Radeny, and Kinyangi, 2013). While it is often viewed as a climate–smart practice, particularly when supported by irrigation systems (Tesfaye *et al.*, 2023). As a result, adaptation efforts have primarily concentrated on other crops and livestock farming (Asfew & Bedemo, 2022; Berhanu *et al.*, 2024; Di Falco & Veronesi, 2013; Mpala & Simatele, 2024). However, recent studies indicate that horticultural farming remains susceptible to climate change. For instance, horticultural crops are particularly vulnerable to climate change due to their high water demands and specific temperature requirements (Patrick *et al.*, 2020). Increasing temperatures may exceed crop–specific thresholds, thereby impacting growth and yield. For example, higher temperatures can reduce tomatoes' yield and quality (Ayankojo & Morgan, 2020). Changes in rainfall patterns result in greater variability in water availability, which subsequently affects crop growth and irrigation needs (OECD, 2014).

As a result, climate–smart agriculture practices (CSA) have been introduced and implemented to adapt the adverse effects of climate change on agricultural productivity. CSA acts as a bridge between scientific research and policymaking, contributing to accomplishing sustainable development goals, initially pioneered by FAO in 2010 at the Hague Conference on Agriculture,

[1] Department of Agricultural and Resource Economics, Graduate School of Bioresource and Bioenvironmental Sciences, Kyushu University, Japan
[2] Department of Agricultural Economics, Debre Tabor University, Ethiopia
[3] Department of Agricultural and Resource Economics, Faculty of Agriculture, Kyushu University, Japan
[4] Alexander von Humboldt Research Fellow at Leibniz–Centre for Agricultural Landscape Research (ZALF), Müncheberg, Germany
[5] Okinawa Institute of Science and Technology Graduate University (OIST), Japan
* Corresponding author: H. Nomura (Email: hnomura@agr.kyushu–u.ac.jp)

Food Security, and Climate Change (FAO, 2013). CSA practices refer to sustainably transforming, reorienting, and creating long–term agricultural development, improving yield and household welfare. Developing countries, including Ethiopia, have embraced various climate–smart agriculture (CSA) practices as adaptation strategies to tackle these challenges (Waaswa *et al.*, 2021). CSA practices have been widely implemented for their effectiveness in mitigating the adverse effects of climate change by enhancing resilience and farm production while lowering greenhouse gas emissions (Di Falco and Veronesi, 2013; FAO, 2022). Different countries have been practicing CSH in various groups, such as innovative agronomic methods (adjusting irrigation scheduling[6], managing pests and diseases, using improved varieties adapted to climate variability, implementing crop rotation, and changing planting and harvest dates) by Shah & Wu (2019), soil conservation practices such as using compost, mulching, organic fertilizers, and conservation agriculture, tie ridge by Okoronkwo *et al.* (2024) and farm risk reduction practices (crop insurance, crop diversification, and utilizing water ponds on their farm plots) (Naazie *et al.*, 2023). Since horticulture crops are being influenced by climate change and the need for targeted adaptation strategies to enhance their resilience and long–term sustainability, recently, the concept of climate–smart horticulture (CSH) practices has been customized from the CSA concept. It has a similar definition of CSA, which follows the same principles of adaptability and building resilience to climate variability. However, the CSH concept involves adapting and building the resilience of horticulture crops to climate variability (Mwikamba, Otieno, and Oluoch–Kosura, 2024).

Moreover, the Ethiopian and Japanese governments have collaborated to implement market–oriented extension programs called Smallholder Horticulture Empowerment and Promotion (SHEP) to improve farmers' income and welfare. The primary focus of the SHEP program is to facilitate and teach farmers to adopt a "*grow to sell*" approach, which involves farmers continuously analyzing market demand before they grow strategic[7] horticultural crops, rather than simply planting crops business as usual. The SHEP program has provided various comprehensive soft skills training, including sensitization workshops (which clearly communicate the vision), market demand analysis, improved agronomic training (covering crop selection, crop calendar, soil management, planting protocols, weed management, pest and disease control, and harvesting techniques), post–harvest handling, profitability analysis, gender mainstreaming, and other climate–smart agricultural practices. The SHEP interventions have also been implemented to improve horticultural crop yield, equipping farmers with essential skills and knowledge to make informed production decisions aligned with the market demand within climate–variability scenarios. Thus, the SHEP intervention significantly promotes commercialization and joint decision–making, thereby improving the income of smallholder farmers (Fikadu *et al.*, 2025). On the other hand, even though CSH practices are not a frontline objective of the SHEP program, they have broadly been promoted in every single training session of the SHEP program. For example, using disease–resistant varieties, diversifying market–demand horticulture crops, adjusting planting and harvesting time, adjusting irrigation schedules, and other climate–smart practices have been provided to the farmers as integral sections of the SHEP training packages (Nomura *et al.*, 2024). In line with this, the SHEP intervention promotes climate–smart horticulture (CSH) practices to increase productivity, adapt to agricultural risks, which are called adapting climate–related risks (Nomura *et al.*, 2024), and improve household income (Fikadu *et al.*, 2025).

Despite the growing body of literature on adopting climate–smart agriculture (CSA) practices and their effects on crop yield, few studies have focused on examining the effects of adopting CSH practices on horticultural yield. For example, the research conducted by Mwikamba, Otieno, and Oluoch–Kosura (2024) highlighted the factors affecting adopting CSH practices in Kenya. They treated the data as count data and employed a negative binomial regression model, but did not address how these practices influence horticultural crop yield. Nevertheless, the effects of adopting CSH practices on horticultural yield, especially within irrigation–based horticultural farming using methodologically rigorous approaches, have been less documented. Addressing these gaps by analyzing the effects of CSH adoption on horticultural yield will provide a more comprehensive understanding of sustainable horticultural farming. A study by Nomura *et al.* (2024) confirmed that adopting the Smallholder Horticulture Empowerment and Promotion (SHEP) approach enhances the likelihood of adopting agricultural practices to manage climate–related risks following climate–smart principles. However, the heterogeneous effects of the SHEP approach through adopting CSH practices remain underexplored. Therefore, this study aims to estimate the effects of farmers' adoption of climate–smart horticulture practices and SHEP intervention on aggregate weighted horticultural crop yield.

Conceptual framework of the study

The conceptual framework illustrates how the SHEP intervention affects aggregate weighted horticultural

[6] **Irrigation schedule adjustment** is implemented among groups of farmers who have irrigation plots within the same cluster and share similar water sources in our study areas. Adjusting the schedule based on a commonly agreed rotation system facilitates the efficient use of limited water resources, minimizing wastage and ensuring that all farmers can conveniently access water at different times.

[7] **Market–responsive horticultural crops** refer to market–driven crop types selected by farmers based on their high demand, profitability, and suitability to local agroecological conditions. In the SHEP framework, diversification emphasizes strategically selecting high–value horticultural crops to maximize income and market responsibness rather than producing a wide array of crops regardless of their market demand.

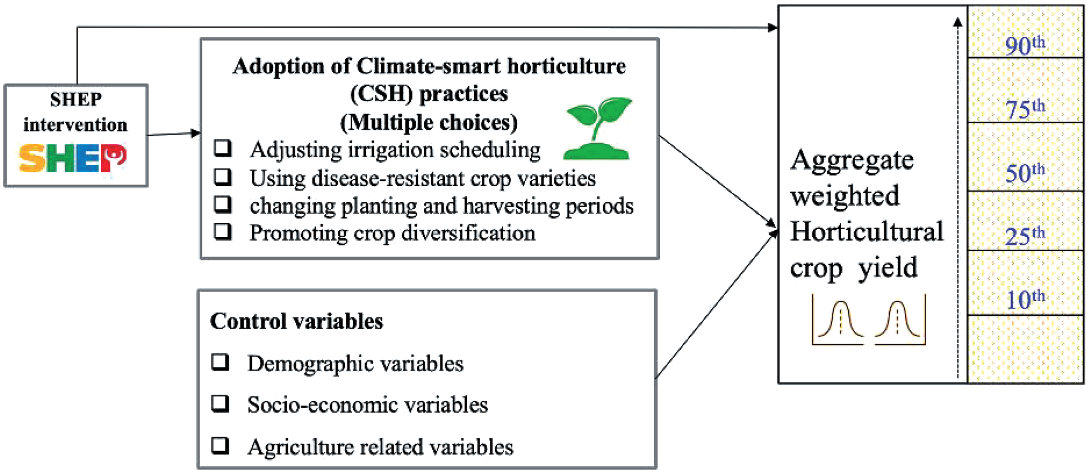

Fig. 1. Conceptual framework of the effects of adoption of CSH on aggregate weighted horticulture yield.

yield through adopting climate–smart horticulture (CSH) practices, such as adjusting irrigation scheduling, using disease–resistant crop varieties, adjusting planting and harvesting times, and market–oriented crop diversification[8] (Fig. 1). The study employs inverse probability–weighted regression adjustment (IPWRA) to estimate average treatment effects by addressing selection bias. We use quantile regression as a regression adjustment after matching instead of ordinary least squares (OLS) to capture the heterogeneous effects of SHEP and CSH adoption across the yield distribution. The framework also considers how farmers' demographic, socioeconomic, and agriculture–related characteristics influence aggregate weighted horticultural yield across different quantiles, from the lowest to the highest.

RESEARCH METHODS

Study area setting, sampling procedures, and data

The SHEP intervention has been implemented in four woredas (districts) and eight kebeles[9] within the Jimma zone of the Oromia region. The intervention kebeles were not randomly selected when the project was initially launched, introducing potential selection bias in assessing its effect on horticulture yield. Therefore, we employ a quasi–experimental research design (QERD) to control for selection bias at the kebele level. Unlike randomized control trials (RCTs), QERD lacks randomization and instead uses agricultural peculiarities or observable characteristics deliberately employed to select or match counterfactual groups with the treated groups. We utilized various agricultural peculiarities, including soil properties, slope, elevation, irrigation availability, distance to major cities, and road density, to create equivalent counterfactual kebeles alongside treated kebeles using satellite geographic information system (GIS) (Campbell & Stanley, 1963). These parameters are considered essential for improving horticultural production and marketing. Based on those agricultural peculiarities, we created a comparable counterfactual group outside the SHEP intervention woreda, referred to as "control" groups. The main assumption is that individuals in the control group are expected to be located far from the SHEP intervention areas, leading to minimal social interactions or information sharing among farmers, thus helping to prevent potential spillover effects. We followed several procedures to identify counterfactual kebeles. First, we divided the entire Oromia region into a grid of 1 km by 1 km parcels. We assigned a dummy value of 1 to parcels within the kebeles with SHEP interventions, designating these as "treated" parcels. All other parcels received a dummy value of 0, representing the "non–treated" parcels. Second, we considered six essential agricultural characteristics or non–random attributes, such as soil characteristics and access to infrastructure, at the 1 km by 1 km parcel level for both treated and non–treated parcels. Third, using R programming software, we applied the nearest neighbor matching method at the 1 km by 1 km mesh level to statistically identify control parcels that resemble the "treated" parcels based on these key attributes. Fourth, we calculated the total number of plots of 1 km by 1 km identified as "control" for each "no treatment" kebele in the non–intervention woredas,

[8] Crop diversification can be classified into two types. **Conventional crop diversification** involves growing a variety of crops primarily to reduce risks, such as crop failure, without necessarily considering market demand or profitability. In contrast, **market–responsive crop diversification** entails the deliberate selection of crops based on market demand and profitability, aiming to maximize income by focusing on more marketable crops.

[9] Ethiopia's administrative system is organized hierarchically into four levels of authority: regions, zones, woredas (districts), and kebeles, with the kebele being the smallest administrative unit.

respectively. Finally, we designated a kebele as a "control" kebele if more than 20% similar to those treated kebeles, highlighting the confounding factors between the treated and counterfactual groups to become more comparable (Fig. 2 and Appendix 1). Thus, this study used 15 kebeles (eight treated and seven control kebeles) across six woredas, comprising 409 smallholder farmers in horticulture (207 from the treated group and 202 from the pure control group) (Fig. 2). Household survey data were collected using structured questionnaires from December 2022 to January 2023.

Main variables of interest and their measurement
Aggregate weighted horticulture yield

Weighting in aggregate yield estimation is crucial in contexts where farmers cultivate multiple horticultural crops within the same season; for example, farmers in the study area have grown different horticultural crops, such as cabbage, onion, potato, tomato, carrot, sweet potato, and green pepper, on separate plots. It ensures that crops occupying a larger share of land contribute more to the overall measure. This approach enhances comparability across households by standardizing yield metrics and preventing distortions caused by crops from small plots. Additionally, it balances representation by mitigating the risk of overinflating yield for high–yield crops grown on small plots while ensuring that low–yield crops cultivated in larger areas are not underrepresented. Furthermore, the sample size in this study for each horticultural crop is small, which is insufficient for econometric model estimation for the individual crop; therefore, we use the aggregate weighted yield to represent overall household–level horticultural yield. The ratio of land allocated for each crop to the total horticultural land of the household serves as a weighting factor, acting as a proxy for the relative importance of each crop in the farmer's production strategy. We follow the following three steps to calculate the household production system's aggregate weighted yield of the horticultural crops.

First, we calculate the yield of each crop produced by the farmers, which is the ratio of the quantity of harvests multiplied by the land allocation of each crop.

$$(Yield)_{ij} = \frac{(Quantity\ of\ harvest\ measured\ in\ kg)_{ij}}{(Land\ area\ measured\ in\ hectare)_{ij}} \tag{1}$$

Where j denotes the horticultural crop types produced by farmer i.

Second, we calculate the weighting factor for each crop to estimate the aggregate yield of farmers' horticulture crops.

$$(\text{Weight})_{ij} = \frac{(\text{Land allocation})_{ij}}{(\text{Lotal land size for horticulture production})_{ij}} \tag{2}$$

Third, we aggregate the yield of each crop using the weight factor for the individual farmers who produced them in the same season. This approach accounts for

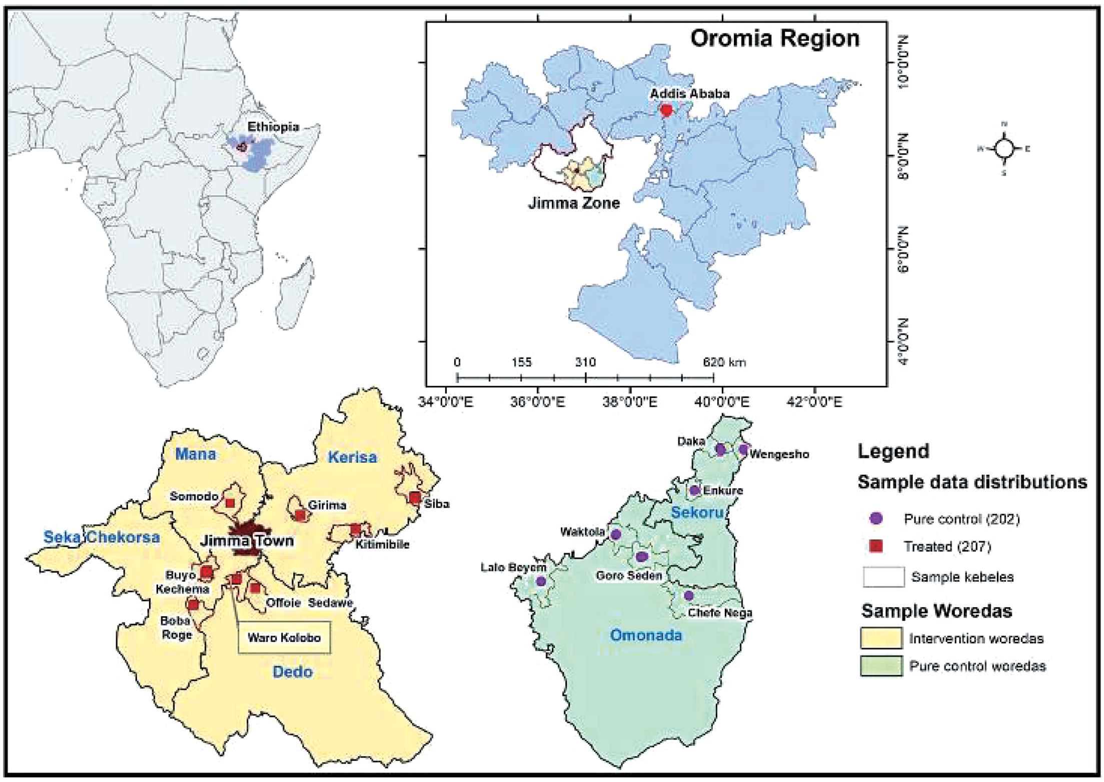

Fig. 2. Map of the study areas.
Source: Sketched by the authors (2024)

the relative importance of each crop based on land allocation decisions. It provides a balanced representation of all crops, preventing overemphasis on high–yielding crops that might occupy smaller areas.

$$(\text{Aggregate weighted horticultural yield})_i = \sum_{j=1}^{7} [(\text{Weight})_{ij} * (\text{Yield})_{ij}] \quad (3)$$

Where i represents the sample farmers and j denotes the number of horticultural crops produced by the sample farmers.

Adoption of climate–smart horticulture (CSH) practices

In this study, the adoption of CSH practices is measured using dummies (adopters and non–adopters) for each practice implemented by farmers, such as adjusting irrigation scheduling, using disease–resistant crop varieties, adjusting planting and harvesting times, and diversifying crops for market orientation. A farmer is considered an adopter if they employed at least one CSH practice, while those who did not implement any CSH practices at all are referred to as non–adopters.

Econometric model specification

We used an inverse probability weighting regression adjustment to estimate effects of adopting CSH practices on aggregate weighted horticultural yield.

Inverse Probability Weighting Regression Adjustment (IPWRA)

We used the Inverse Probability Weighted Regression Adjustment (IPWRA) model to estimate the effects of adopting CSH practices in a quasi–experimental design setting, which makes a causal inference by creating the best possible counterfactual groups. The IPWRA estimates the Average Treatment Effects on the treated, which is the difference in outcome variables of the adopters and non–adopters, and it helps as a "therapy" for biases that arise from misspecification of Propensity Score Matching (PSM) (Ogunniyi *et al.*, 2023). Misspecification of the propensity score model occurs when important covariates are excluded, irrelevant ones are included, or nonlinear relationships are assumed linear, leading to poor covariate balance and biased treatment effect estimates. Similarly, the outcome model may suffer from missing key covariates, including irrelevant ones, or failing to capture nonlinear or heterogeneous effects, resulting in biased estimates of the Average Treatment Effect on the treated (ATET). These issues compromise the accuracy of both models, as the propensity score fails to balance treated and untreated groups, and the outcome model misestimates the relationship between covariates and outcomes. The IPWRA estimator is a "doubly robust" model, indicating that consistent treatment effects can be estimated even if one of the two models (treatment and outcome model) is incorrectly specified (Sibhatu, Arslan, and Zucchini, 2022; Wooldridge, 2010). Thus, this estimator allows us to estimate the effects of smallholder farmers' adopting CSH practices on horticulture production.

Following Ogunniyi *et al.* (2023), we assume the linear regression function of the model estimation is $Y_{ij} = \beta_i + \gamma_i X_i + \varepsilon_i$. Then, we follow three steps to estimate ATET using the IWPRA: First, we generate the propensity score using the observable factors $p(x; \widehat{y})$. Second, we calculate the weights for the adopters and non–adopters using the inverse of the propensity score values to create balanced pseudo–populations, such as weights for the treated group $1/p(x; \hat{y})$ and weights for the control group (Fig. 3). Third, we estimate the Average Treated Effects on the Treated (ATET) using inverse probability weighted least squares from the adopters and non–adopters.

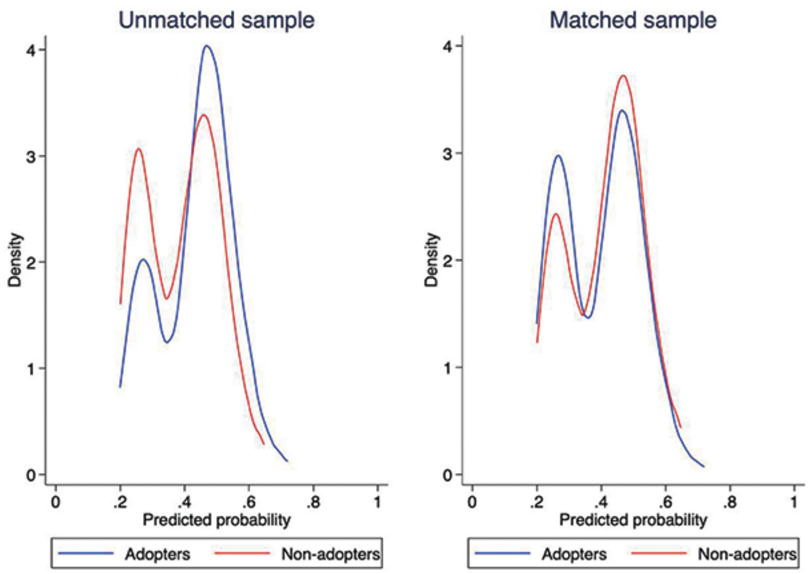

Fig. 3. Testing the overlap assumption before and after matching

$$\min_{\beta_1 \gamma_1} \sum_{i=1}^{n} (Z_i - \beta_1 - \gamma_1 X_i) / p(x; \widehat{y}) \text{ if } T_i = 1 \quad (4)$$

$$\min_{\beta_0 \gamma_0} \sum_{i=1}^{n} (Z_i - \beta_0 - \gamma_0 X_i) / p(x; \widehat{y}) \text{ if } T_i = 0 \quad (5)$$

where (β_1, γ_1) is the estimation for the adapters or T_i =1) and (β_0, γ_0) is the estimation of non–adapters or T_i =1.

Then, estimate the ATET, which is the difference between equations 8 and 9.

$$ATT = \frac{1}{n_t} \sum_{i=1}^{n_t} [(\hat{\beta}_1 - \hat{\beta}_0)] (\hat{\gamma}_1 - \hat{\gamma}_0) X_i \quad (6)$$

where n_t is the total number of smallholder farmers who adopted the CSH practices, ($\hat{\beta}_1 \hat{\gamma}_1$) denotes the estimated inverse probability weighted parameters for the adopters are denoted, and ($\hat{\beta}_0 \hat{\gamma}_0$) and represents the estimated inverse probability weighted parameters for the non–adopters.

Fourth, quantile regression is estimated as a regression adjustment by including the treatment and other control covariates to assess the robustness of the ATET.

$$Y_i = \beta_i + \theta_i T_i + \omega_i D_i + \gamma_i X_i + \varepsilon_i \quad (7)$$

where T_t is the treatment variable (adoption of CSH practices), and D_i is the SHEP intervention (1 = treated and 0 = otherwise) X_i are other control variables.

The outcome variables (Y_i) in this model (IWRA) are aggregate weighted horticultural yield. All sample farmers are included in estimating the Average Treatment Effect on the Treated (ATET) of adoption to Climate–Smart Horticulture (CSH) practices on aggregated horticultural production.

After estimating the Average Treatment Effect on the Treated (ATET) using the Inverse Probability Weighted Regression Adjustment (IPWRA), we further investigate the factors influencing aggregated weighted horticultural yield through quantile regression because the study setting is a quasi–experiment, there is still some confounding bias (hidden bias) that has been inherited after IPW matching. The rationale for using quantile regression arises from our findings on the Average Treatment Effect (ATE), which reveal that the benefits of adopting CSH practices are not uniform across all smallholder farmers. The mean–based estimators may obscure these heterogeneous effects. In contrast, quantile regression allows us to examine how the effects of various factors differ across the aggregate yield distribution—from the lowest to the highest quantiles. In quantile regression estimation, we decompose the adoptions of CSH practices into four practices: adjusting irrigation schedule, using disease–resistant crops/varieties, changing sowing and harvesting time, and using crop diversification. Quantile regression shows the heterogeneity effects of the covariates, providing insights into effects at different aggregate weighted yield distributions, from the lowest to highest levels (Buchinsky, 1998; Fikadu *et al*., 2025; Koenker & Hallock, 2001; Ogutu & Qaim, 2019). Following Tabe Ojong *et al*. (2022), the standard quantiles were used, encompassing the median (50th percentile), quartiles (25th and 75th percentiles), and two additional percentiles—one at the lower end and another at the upper–income level (the 10th, 25th, 50th, 75th, and 90th quantiles).

The quantile regression specification is explained in Equation (4):

$$Y_i = X_i' \beta_q + \mu_{qi} \quad \text{where; } (Y_i \mid X_i = X_i' \beta_q) \text{ ------------ } (8)$$

where Y_i is the aggregate weighted yield; X_i is the set of covariates, including different adoptions of CSH practices, SHEP intervention, Interaction effects, and other control covariates such as farmers' socioeconomic, demographic, and institutional characteristics; q it is a quantile with $0< q<1$ β_q the parameters to be estimated.

RESULTS AND DISCUSSIONS

Summary of descriptive statistics

Table 1 summarizes various covariates across adopters and non–adopters, highlighting the statistically significant differences between the two groups. The average education level of the household head was over three years, while non–adopters were below three years, suggesting that better education may influence adoption decisions. The average land area allocated for horticulture production is 0.56 hectares, which is almost similar for both adopters and non–adopters. The average years of experience in horticulture farming for adopters were over eight years, whereas non–adopters had seven years, which is a statistically significant mean difference between them. The farmers who have more years of experience might have contributed to the likelihood of adopting new CSH practices. Approximately 60.7% of the adopters were in the treated group, while about 43.2% were non–adopters, which differs significantly from the control group, indicating that participation in the SHEP intervention is strongly associated with adopting CSH practices. Another essential factor is participation in farm field demonstrations, which is statistically significant; a higher percentage of adopters (65.5%) participated in farm demonstrations compared to non–adopters (53.6%). This emphasizes the role of hands–on learning in adaptation. Similarly, the frequency of extension contact is significant, showing that adopters had more frequent monthly extension visits than non–adopters, suggesting that greater access to agricultural advice facilitates the adoption of CSH practices. The distance to the agriculture office is marginally significant, where adopters are closer to the agriculture office than non–adopters, implying that proximity to the agriculture office may enhance access to resources and support for adopting CSH practices. Livestock ownership, measured in Tropical Livestock Units (TLU), is statistically significant, showing that adopters own more livestock than non–adopters, suggesting that wealthier households, regarding livestock assets, are more likely to adopt CSH practices. The baseline difference between adopters and

Table 1. Summary statistics before and after matching

	(1) Full sample	(2) Adopters	(3) Non–adopters	(4) diff (2) – (3)	(5) standardized diff (2) – (3)
Sex of the household head (1 = male; 0 = female)	0.92	0.94	0.93	–0.01	0.00
Age of the household head (years)	42.46	42.59	42.46	0.04	0.01
Education level of the household head (years of schooling)	3.22	3.47	2.99	0.43	0.04
Participation in farm field demonstration in village (1 = yes; 0 = no)	0.64	0.66	0.54	0.19 ***	0.03
Frequency of extension contact (frequency per month)	6.94	7.18	5.69	1.56 **	0.01
Land allocation for horticultural crop production (ha.)	0.56	0.59	0.55	0.03	0.04
Experience of horticulture farming (years)	7.87	8.50	7.36	0.61	0.00
Total family size in the household	6.14	5.99	6.11	–0.06	0.06
Road access (number of months passable for vehicles)	10.81	10.83	10.67	0.24	0.00
Distance to agricultural cooperatives (minutes by foot)	34.84	35.65	40.00	–0.86	0.02
Distance to farmers training center (minutes by foot)	30.00	30.81	29.91	–0.27	0.05
Distance to main market (minutes by foot)	78.07	77.98	79.45	4.41	–0.01
Distance to agriculture office (minutes by foot)	29.87	28.08	31.18	–3.10 **	0.01
Livestock (in TLU)	4.16	4.37	3.75	0.49 *	0.01

non–adopters was removed after applying matching (ipw), which indicates that their characteristics are well balanced. After matching, the standardized mean differences should be consistently below 0.1 and not statistically significant for successful matching (Austin, 2009).

Association between adopting CSH practices and SHEP intervention

We observed a consistent trend of higher adoption of different practices among farmers in the treated group compared to those in the control group. The adoption of irrigation schedule adjustments varies significantly between the control and treated groups, with approximately 13% of farmers in the treated group making this adjustment, compared to 2.9% in the control group (Fig. 4A). This indicates that participation in the treatment (SHEP intervention) slightly increases the likelihood of adopting irrigation schedule adjustments, though overall adoption remains relatively low. Adopting disease–resistant crop varieties is more prevalent than adjusting irrigation schedules, with adoption rates of 38.7% in the treated groups and 28.7% in the control groups (Fig. 4B). This implies that farmers in the SHEP intervention are more inclined to adopt disease–resistant crop varieties to mitigate disease risks than those in the control group. Adjusting sowing and harvesting times represents another adaptation strategy that entails modest decision–making. Farmers in the treated group adopted their sowing and harvesting times at a rate of 21.7%, while those in the control group reached 14.4% (Fig. 4C). This disparity indicates that SHEP participants made more informed adoption decisions regarding planting schedules in response to climate variability. This shift suggests the intervention's positive, albeit limited, impact on promoting adaptive agronomic practices. Crop diversification, a vital risk management strategy, exhibits the lowest adoption rates among all practices. In the treated group, only 15.9% of farmers utilized crop diversification as a CSH practice, whereas 5.4% of farmers in the control group adopted it (Figure 4D).

Aggregate weighted horticulture yield across adopters of CSH practices and SHEP groups

Fig. 5 shows the red line (Non–adopters: Control), which shows the highest peak, indicating a larger proportion of individuals with very low horticultural yields (up to 2,000 kg). The green line (Non–adopters: Treated) shifts slightly to the right compared to the red line, suggesting that treatment positively influences the aggregate weighted horticultural yield of non–adopters. The blue line (Adopters: Control) is skewed to the left but has a longer tail, implying that adopters without treatment achieve higher production levels than non–adopters. The purple line (Adopters: Treated) shifts further to the right and has the flattest distribution, signifying a significant improvement in the horticultural yield of adopters due to treatment. Thus, adopters (from treated and control) consistently demonstrate higher production levels than non–adopters, underscoring the benefits of adopting climate–smart horticultural (CSH) practices. Moreover, the shift from blue (Adopters: Control) to purple (Adopters: Treated) is more pronounced than the shift from red (Non–adopters: Control) to green (Non–adopters: Treated), suggesting that treatment is more effective for adopters compared to non–adopters.

Average treatment effects of adopting CSH practices on aggregated weighted horticultural crop yield

Table 2 presents the estimated impact of adopting Climate–Smart Horticulture (CSH) practices on aggre-

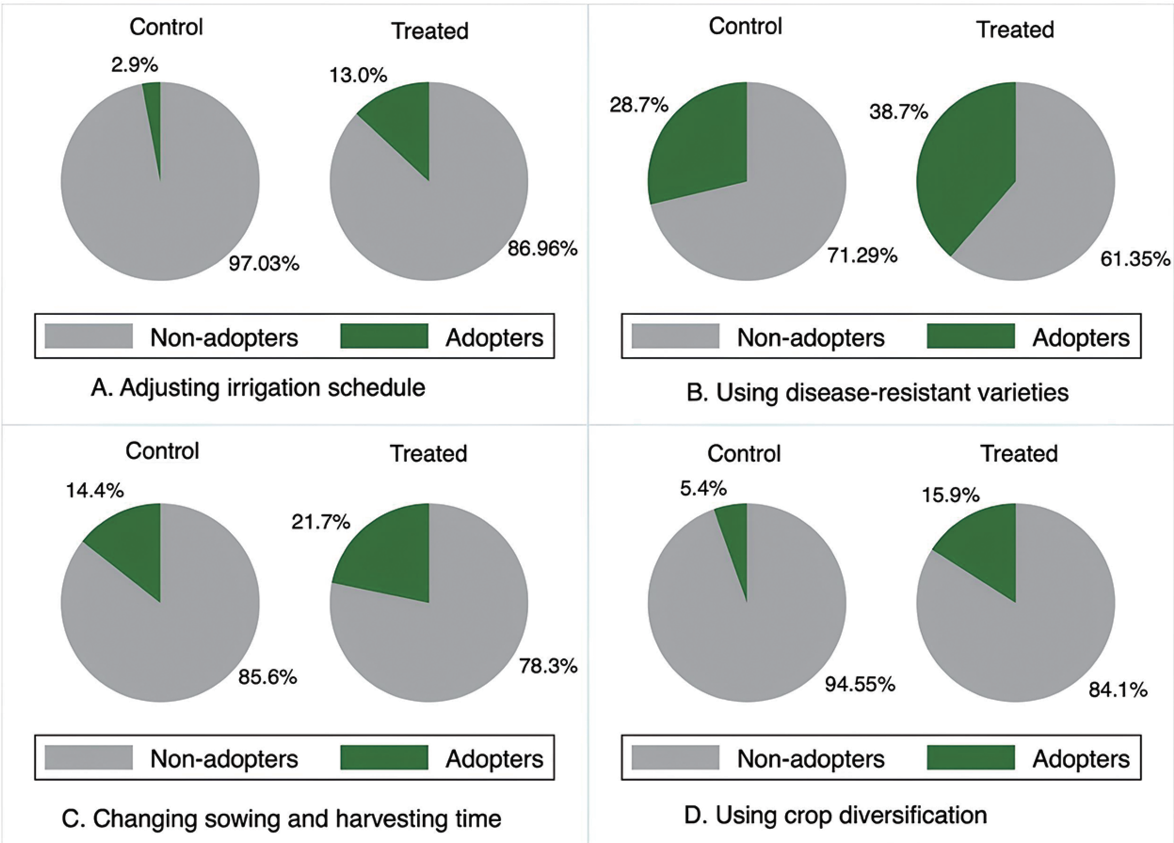

Fig. 4. Adoption of different climate-smart horticulture (CSH) practices across the SHEP group.

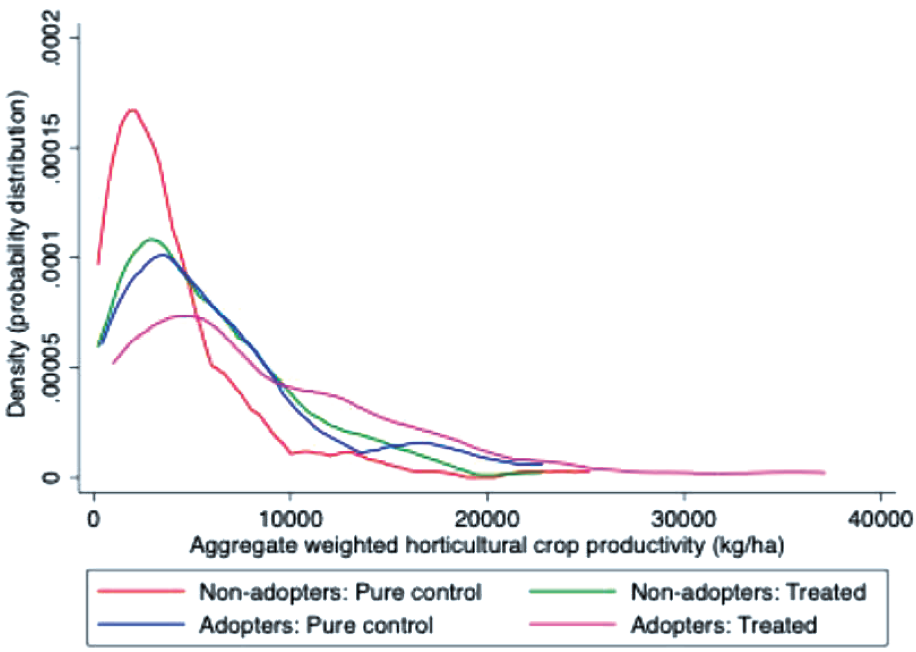

Fig. 5. The results of Kernel density estimation: Distribution of horticultural production between adapters and non-adapters in SHEP groups.

Table 2. Average treatment effect of adopting CSH practices on aggregated weighted horticulture yield

	ATET	POMean	ATE	POMean
Adaptation of CSH	0.430	8.177	0.059	8.248
practices	(0.086) ***	(0.072) ***	(0.051)	(0.053) ***

gate weighted horticultural yield, using Inverse Probability Weighted Regression Adjustment (IPWRA). The Average Treatment Effect on the Treated (ATET) is 0.430, meaning that CSH adopters experience a 43.0% increase in yield compared to what they would have experienced had they not adopted these practices. This confirms that adopting CSH practices significantly enhances yield among those who adopt them. The Average Treatment Effect (ATE) is 0.059, indicating that when considering the entire population, the overall effect of adopting CSH practices is only a 5.9% increase and is statistically insignificant, which suggests that while adopting CSH practices is highly beneficial for adopters, expanding it to all farmers may not give the same level of adoption. Compared to the value of ATET, the small and insignificant ATE highlights heterogeneous treatment effects, meaning that certain farmers could benefit more from adopting CSH practices than others. Thus, this finding underscores that CSH adoption is highly effective for those who voluntarily adopt it. However, its benefits might not be uniform across all farmers; it will likely be heterogeneous. Consequently, rather than promoting broad or blanket climate change adaptation policies (one–size–fits–all), policymakers should focus on context–specific, location–sensitive CSH interventions. This approach ensures that CSH adaptation strategies align with different farming communities' socioeconomic and agroecological conditions, maximizing their effectiveness and long–term sustainability. Moreover, the potential outcome means (POMean) for adopters and non–adopters provides additional insights into the post–treatment yield levels. The expected yield level for adopters is 8.177, while for the entire population (adopters and non–adopters), it is 8.248. This suggests that the estimated yield levels between the two groups remain relatively comparable in absolute terms after accounting for selection bias. However, the positive and significant ATET effect indicates that adopters achieve a notable relative advantage due to adopting CSH practices.

Heterogeneous effects of adopting CSH practices and SHEP intervention on aggregated horticulture yield

We decompose the CSH practices into four components: (i) adjusting irrigation schedules, (ii) using disease–resistant crop varieties, (iii) adjusting planting and harvesting periods, and (iv) implementing crop diversification. This disaggregation enables a nuanced assessment of their effects on aggregated weighted horticultural yield (Table 3). By disaggregating CSH practices, we provide a more realistic representation of farmers' decision–making processes, as adoption is often selective rather than uniform. Farmers tailor their choices based on specific agroecological conditions, resource availability, and market incentives, resulting in varying impacts on horticultural yield. This nuanced approach enhances the understanding of diverse adaptation pathways, offering more targeted insights for policy and extension services.

Our findings indicate varied results regarding the effects of adopting various CSH practices through the SHEP intervention on aggregated weighted yield. For example, the SHEP intervention positively influences aggregate weighted horticultural yield across all quantiles except the 10^{th} quantile, regardless of whether farmers adopt CSH practices (Table 3: model–1). Moreover, the interaction effects of the SHEP intervention and the use of disease–resistant crop varieties are notably significant at the 75^{th} quantile of aggregate weighted horticultural yield, suggesting that farmers in the higher yield range benefit the most from the synergy between market–oriented extensions like the SHEP intervention and climate–resilient crop choices, such as adopting disease–resistant crops (Table 3: model–2). On the other hand, the interaction effects of SHEP and crop diversification show reverse effects on aggregate yield, indicating that adopters in the control group exhibit higher aggregate weighted yield per hectare than those in the treated group.

Road access has a significant heterogeneous effect on aggregate weighted yield across all quantiles except for the lowest (10^{th} quantile), indicating that better road infrastructure benefits most farmers by enhancing their aggregated horticulture yield (Table 3). The distances to agricultural cooperatives and farmers' training schools are crucial factors affecting horticulture yield, particularly in the higher quantiles, such as the 75^{th} and 90^{th} percentiles (Table 3: model–2).

DISCUSSIONS

This study examines the effects of SHEP intervention and the adoption of CSH practices on aggregate horticultural crop yield. Our findings demonstrate that adopting various CSH practices through the SHEP intervention has different effects on the aggregate weighted horticultural yield, implying that these effects depend on the specific CSH practices implemented. On the one hand, the SHEP intervention boosts yield across all quantiles except the 10^{th} quantiles, regardless of the interaction effects of farmers' adoption of CSH practices. Furthermore, the interaction between the SHEP intervention and the adoption of disease–resistant crop varieties shows a significant positive effect at the 75^{th} quantile, indicating that farmers with higher yields benefit the

Table 3. Factors affecting aggregated weighted horticulture yield using quantile regression estimation

	10th		**25th**		**50th**		**75th**		**90th**	
Covariates	**Model–1**	**Model–2**	**Model–1**	**Model–2**	**Model–1**	**Model–2**	**Model–1**	**Model–2**	**Model–1**	**Model–2**
	$\hat{\beta}$ (SE)	**$\hat{\beta}$ (SE)**	**$\hat{\beta}$ (SE)**	**$\hat{\beta}$ (SE)**	**$\hat{\beta}$ (SE)**	**$\hat{\beta}$ (SE)**	**$\hat{\beta}$ (SE)**	**$\hat{\beta}$ (SE)**	**$\hat{\beta}$ (SE)**	**$\hat{\beta}$ (SE)**
SHEP intervention (1= treated group; 0= control group)	0.740 (0.137)	1.016 (0.241)***	0.520 (0.149)***	0.627 (0.188)***	0.419 (0.117)***	0.497 (0.135)***	0.347 (0.072)***	0.388 (0.114)***	0.406 (0.101)***	0.375 (0.144)**
Adjusting irrigation schedule (1= yes; 0= no)	–0.451 (0.316)	0.052 (0.287)	–0.365 (0.138)***	–0.432 (0.962)	–0.436 (0.241)*	–0.519 (0.252)**	0.014 (0.358)	–0.449 (0.203)**	0.066 (0.123)	–0.453 (0.841)
SHEP intervention * Optimizing the irrigation schedule		–0.628 (0.391)		0.086 (0.982)		0.188 (0.386)		0.588 (0.448)		0.493 (0.858)
Use of disease–resistant varieties (1=yes; 0=no)	0.541 (0.147)***	0.869 (0.346)**	0.320 (0.136)**	0.650 (0.303)**	0.270 (0.131)**	0.254 (0.145)*	0.199 (0.098)**	0.047 (0.134)	0.087 (0.114)	–0.031 (0.159)
SHEP intervention * Use of disease–resistant varieties		–0.349 (0.372)		–0.419 (0.339)		–0.023 (0.226)		0.309 (0.181)*		0.193 (0.185)
Adjusting the sowing and harvesting time (use effective crop calender) (1= yes; 0= no)	0.392 (0.142)***	0.291 (0.347)	0.169 (0.139)	0.006 (0.382)	0.127 (0.199)	0.266 (0.278)	0.280 (0.104)***	0.540 (0.152)***	0.143 (0.115)	0.282 (0.147)*
SHEP intervention * Adjusting the sowing and harvesting time		0.156 (0.358)		0.171 (0.409)		–0.228 (0.335)		–0.312 (0.331)		–0.116 (0.181)
Use of crop diversification (1= yes; 0= no)	–0.135 (0.159)	–0.286 (0.643)	0.024 (0.335)	0.009 (0.320)	0.370 (0.238)	1.052 (0.828)	0.370 (0.069)***	1.132 (0.096)***	0.146 (0.225)	1.017 (0.243)***
SHEP intervention * Use of crop diversification		0.109 (0.665)		0.058 (0.493)		–0.699 (0.845)		–1.000 (0.187)***		–1.024 (0.258)***
Sex of the housheold head (1=male; 0=female)	0.169 (0.242)	0.177 (0.179)	0.001 (0.202)	0.024 (0.230)	0.077 (0.282)	0.069 (0.291)	0.023 (0.110)	–0.149 (0.112)	0.149 (0.182)	0.138 (0.175)
Age of the housheold head measured in years	0.001 (0.07)	–0.000 (0.005)	–0.011 (0.006) *	–0.012 (0.005) **	–0.001 (0.006)	–0.000 (0.005)	–0.001 (0.003)	–0.002 (0.004)	–0.008 (0.005)	–0.007 (0.004) *
Education level of the household head measured in years of schooling	0.061 (0.022)***	0.049 (0.016)***	0.021 (0.029)	0.032 (0.018)*	0.023 (0.019)	0.016 (0.019)	0.017 (0.011)	0.030 (0.012)**	0.000 (0.017)	–0.004 (0.015)
Total family size in the household	0.006 (0.032)	0.015 (0.023)	0.021 (0.029)	0.009 (0.028)	0.003 (0.028)	–0.013 (0.025)	0.017 (0.018)	0.020 (0.018)	–0.018 (0.020)	–0.015 (0.023)
Road access measured in number of months passable for veheciles	–0.010 (0.034)	–0.022 (0.033)	0.094 (0.041)**	0.095 (0.039)**	0.126 (0.035)***	0.147 (0.031)***	0.106 (0.021)***	0.103 (0.023)***	0.103 (0.035)***	0.086 (0.0279)***
Distance to agricultural cooperatives	–0.003 (0.002)	–0.003 (0.005)	–0.004 (0.004)	–0.005 (0.005)	–0.001 (0.003)	–0.001 (0.003)	–0.002 (0.002)**	–0.004 (0.002)**	–0.004 (0.003)	–0.004 (0.001)***
Distance to farmers training school	0.002 (0.002)	0.002 (0.005)	0.001 (0.005)	0.001 (0.005)	–0.004 (0.004)	–0.003 (0.003)	–0.006 (0.002)**	–0.003 (0.003)	–0.007 (0.003)*	–0.007 (0.003)***
Constant	6.262 (0.560)***	6.190 (0.602)***	6.685 (0.504)***	6.608 (0.528)***	6.730 (0.560)***	6.501 (0.528)***	7.595 (0.289)***	7.670 (0.321)***	8.609 (0.476)***	8.748 (0.422)***
Pseudo R^2	0.1414	0.1495	0.0810	0.0854	0.0957	0.1048	0.1126	0.1305	0.1199	0.1514

Note: Model–1 is the model estimation “without interaction effects”; Model–2 represents model estimation “with interaction effect”; and SE indicates the standard error and $\hat{\beta}$ the coefficients of the covariates. : ***, **, and * show the variables’ significance at 1%, 5%, and 10% significant levels, respectively most from the combined impacts of market–oriented extensions like the SHEP intervention and climate–resilient practices, such as cultivating disease–resistant crops. Disease–resistant varieties reduce yield losses from pests and diseases, especially in intensively managed horticultural systems, which positively influence crop yield (Autio *et al.*, 2021). Alternatively, the interaction between the SHEP intervention and crop diversification adoption demonstrates an inverse effect on aggregate yield, suggesting that adopters in the control group achieve a higher aggregate weighted yield per hectare than those in the treated group. This could be because SHEP is a market–oriented extension approach aimed at helping farmers cultivate crops that align with market demand rather than simply maximizing yields. This market alignment strategy has improved income and food security (Fikadu *et al.*, 2025). Conversely, farmers in the control group, who are not part of SHEP's market–driven strategy, may focus on crops that do not necessarily align with market demand. While such crops may contribute to a higher aggregate yield per hectare, they may not result in greater income gains. This pattern aligns with previous findings from Shimizutani *et al.* (2021), which reported that Kenyan farmers participating in SHEP transitioned to market–responsive crops, leading to a 70% increase in horticultural income despite potential yield reductions. This underscores the notion that SHEP farmers may prioritize market–responsive crop selection over indiscriminate crop diversification for maximizing income, which could explain why adopters in the treated group do not necessarily achieve higher aggregate yield per hectare.

Road access shows a significant heterogeneous effect on aggregate weighted yield across all quantiles, except for the lowest (10^{th} quantile), indicating that improved road infrastructure generally enhances horticultural yield for most farmers. For those in higher yield quantiles, better road access increases the likelihood of generating a marketable surplus by facilitating access to higher–quality inputs. Moreover, a well–developed road network encourages input providers to deliver high–quality agricultural supplies more efficiently, boosting horticultural yield. This result aligns with the findings of Wudad *et al.* (2021); they found that improved road networks allow them to access agricultural inputs, extension services, and higher–value urban markets, further enhancing yield and income gain in Dedo woreda of Jimma zone, Ethiopia.

The proximity to agricultural cooperatives and farmers' training schools is critical in influencing horticultural yield, especially at higher quantiles, such as the 75^{th} and 90^{th} percentiles. It indicates that farmers close to the agricultural cooperatives are more likely to get various agricultural inputs, including improved seed, fertilizer, technical training, and market linkages, which could contribute to higher aggregate yield. Moreover, farmers in the upper yield quantiles tend to possess the resources and knowledge necessary to leverage cooperative membership and training programs fully. This enables them to optimize input usage, adopt advanced agronomic practices, and enhance post–harvest handling. This finding aligns with the study of Akinola *et al.* (2023), who highlighted that farmers who are members of agricultural cooperatives have significantly improved their tomato yield than non–member farmers in Nigeria. In another study by Abate *et al.* (2014), agricultural cooperatives play a crucial role in improving farm efficiency in Ethiopia by providing easy access to improved inputs and embedded supports, including information and training on applying these inputs to their farms. In line with this, the farmer's training center significantly positively affects crop productivity in Ethiopia (Wonde *et al.*, 2022).

CONCLUSIONS AND POLICY IMPLICATIONS

This study examines the relationship between adopting climate–smart horticulture (CSH) practices and participation in the Smallholder Horticulture Empowerment and Promotion (SHEP) intervention. The findings show that 41.3% of farmers adopted CSH practices, with a notably higher adoption rate among the SHEP–treated group (50.7%) than the control group (33.7%). Disaggregated analysis indicates that farmers in the SHEP group more frequently adopt specific CSH practices—such as adjustments to irrigation schedules and disease–resistant crop varieties, as well as adjustments in sowing and harvesting times. However, crop diversification demonstrates the lowest adoption rates among all practices. The SHEP intervention significantly increases the likelihood of adopting irrigation schedule adjustments and crop diversification, emphasizing its market–oriented approach to crop selection. The Average Treatment Effect on the Treated (ATET) reveals a 43.0% increase in yield among adopters compared to non–adopters. The SHEP intervention significantly improved aggregate horticulture yield across all quantiles, regardless of its interaction with CSH adoption. Furthermore, considering the interaction effects of SHEP with adopting CSH practices reveals more significant aggregate yield gains for farmers in the SHEP group who adopt disease–resistant crop varieties. In contrast, the interaction between SHEP and crop diversification is negatively associated with yield, likely due to SHEP's focus on strategic market–oriented crop selection instead of maximizing aggregate yields after addressing hidden biases. Road access, proximity to agricultural cooperatives, and farmers' training schools influence aggregate horticulture yield. These findings underscore the necessity for targeted, market–oriented extension strategies that balance yield optimization with context–specific and market–oriented climate–smart practices rather than applying blanket adaptation policies. Such a strategy would ensure the scalability of CSH practices among smallholder farmers to enhance horticulture yield.

The study provides robust insights into the effects of adopting CSH practices and implementing SHEP interventions to improve horticultural crop yield. We also highlight the heterogeneous effects of various adoption of CSH practices and SHEP interventions on horticultural yield. This study utilized aggregate weighted yield, demonstrating the comparability of aggregate crop yield among smallholder farmers. While the method considers land allocation and offers a balanced representation of all crops, it assumes that weighting by land area adequately reflects the significance of each crop in the farmer's production strategy. This assumption may overlook differences in crop–specific factors such as input intensity, labor requirements, or market value, as the approach aggregates all horticultural crops harvested by smallholder farmers into a single metric. Consequently, valuable insights into the relative performance of specific crops, their economic contributions, and direct comparisons of individual crop yields across farmers will be examined in future research.

AUTHOR CONTRIBUTIONS

Asmiro Abeje Fikadu: Conceptualization; data curation; formal analysis; investigation; Methodology; Validation; Visualization; Writing—original draft; and Writing—review & editing. **Hisako Nomura**: Conceptualization; Data curation; Investigation; Funding acquisition; Methodology; Project administration; Supervision; Validation; and Writing – review & editing. **Girma Gezimu Gebre**: Conceptualization; Data curation; Methodology; Supervision; Validation; and Writing—review & editing. **Payal Shah**: Conceptualization; Data curation; Methodology; Supervision; Writing—review & editing.

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Appendix 1 Summary statistics of key agricultural attributes used in the matching process at kebele level for control group identification

Variables	**Unmatched kebeles**	**Treated kebeles**	**Matched control kebeles**
Soil Clay Depth (%)	36.30	46.37	43.20
Soil Nitrogen Depth (%)	1.61	2.36	1.70
Soil Carbon Depth (%)	24.91	34.10	30.54
Soil pH*10	65.17	56.56	58.69
Distance to nearest major city (km)	317.05	251.43	214.38
Slope (degree)	6.64	5.71	5.64
Elevation (m)	1609.33	1803.35	1721.97
Distance to River (m)	139442.24	65830.29	69727.16
Length road network	1786.18	6425.73	4278.63