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Supporting farmers dealing with climate change: The impact of Participatory Integrated Climate Services for Agriculture (PICSA) on smallholder lead farmers in Malawi

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Abstract

Motivation: The climate crisis threatens the livelihoods and welfare of farmers in the global south. Increasing variability of weather makes it ever more important to get forecasts to farmers and help them make best use of this information. Participatory Integrated Climate Services for Agriculture (PICSA) is an approach that gives farmers better weather forecasts and, in lockstep with agricultural extension workers, supports farmers in interpreting forecasts to make appropriate decisions for their own farms. It has been implemented across more than 20 countries of the global south, including Malawi.
Reviews and evaluations of PICSA have been positive, although it has not previously been rigorously evaluated using impact evaluation techniques.

Purpose: We estimate the impacts of PICSA training and meetings on lead farmers in Malawi, taking farmers in four districts where PICSA operated, and farmers in four other districts where the programme was not present.

Methods: We compare outcomes in farming practice, yields obtained, livelihood decisions and food security between lead farmers who participated in PICSA and those who did not. Because selection into the programme was not random, we use propensity score matching and regression adjustment to correct for potential selection bias.

Findings: PICSA lead farmers used seasonal forecasts to plan farm decisions, change crop activities, increase maize yields, and improve their food security. Differences between them and the control group were, in most cases, significant.
Our results confirm the potential of PICSA to help farmers adapt to climate change.

Policy: In similar contexts, the PICSA approach could effectively support smallholders to make informed agricultural decisions, in participatory discussions, based on climate and weather information.

For Malawi, the evidence suggests the programme or something similar should be continued.

KEYWORDS
agricultural extension, climate change, climate services, climate-smart agriculture, impact evaluation, Malawi, PICSA

1 | INTRODUCTION

Despite the opportunities for growth offered by the adoption of improved agriculture practices, the productivity of smallholder farmers in developing countries is increasingly vulnerable to climate variability, something that will be aggravated by climate change (Jost et al., 2015; Thornton et al., 2014). In the case of Malawi, 81% of the population lives in rural areas, with the majority (89%) of households engaged in agriculture (NSO, 2017). Furthermore, agriculture is almost exclusively rain-fed: estimated irrigated land varies from 0.2% to 4% (World Bank, 2018).

The country is also particularly prone to natural hazards. Since the 1990s Malawi has experienced a wide range of climatic shocks including the 1991–1992 drought and a famine in 2001–2002. More recent anomalies include the 2015–2016 rainy season which started with a delay of two to four weeks, followed by short and erratic rains. The government declared a state of emergency due to the resulting humanitarian disaster, estimating that at least 6.5 million people (39% of the population) would be unable to meet their food requirements (World Bank et al., 2016). The following agricultural cycle in 2017–2018 was also subject to erratic rains and was plagued by infestations of fall armyworms (*Spodoptera frugiperda*), causing an estimated crop loss of 20% (World Bank, 2018).

In 2017, the United Nations Development Programme (UNDP), in partnership with the Government of Malawi through the Department of Disaster Management Affairs and with funding from the Green Climate Fund, launched the Saving Lives and Protecting Agriculture-Based Livelihoods in Malawi: Scaling Up the Use of Modernized Climate Information and Early Warning Systems (M-CLIMES) project (UNDP, 2024). Besides strengthening the capacity of the hydro-meteorological network and improving the accuracy of weather and climate data in the country, the project aims to benefit farmers by providing customized seasonal forecasts and directly delivering weather and agricultural recommendations.

A component of the M-CLIMES project is PICSA, an intervention designed by the University of Reading (UoR). PICSA uses a training of trainers (ToT) extension model and makes use of forecasts and participatory decision-making tools to empower farmers in the face of climate change. To date, this approach has been adapted and put into action in more than 20 countries (Clarkson et al., 2022).

Participatory and qualitative assessments of PICSA suggest large returns for farmer households on a variety of aspects, ranging from better-informed crop and livestock adaptation choices to increased yields and profits (see Clarkson et al., 2017; Clarkson et al., 2022; Dayamba et al., 2018). However, to the best of our knowledge, substantial evidence on the impact of the provision of participatory-based climate services has yet to be established.

Based on a multi-stakeholder collaboration convened by the Learning-Oriented Real-Time Impact Assessment (LORTA) programme of the Independent Evaluation Unit of the Green Climate Fund, this article makes a modest start to filling this gap by studying the impact of PICSA on farmer households' outcomes across eight districts in Malawi. We use propensity score matching and regression adjustment methods, using observable characteristics, to control for potential selection bias. Specifically, we apply nearest-neighbour matching (with replacement), distance-weighted radius matching (with regression adjustment), and doubly robust inverse-weighted estimations to a sample of 348 lead farmers in eight districts of Malawi. We evaluate the impact of PICSA as delivered through training-of-trainers using a farming systems approach to understand and support smallholder decision-making.

Our results suggest that PICSA effectively empowered lead farmers in Malawi, by allowing them to make climate-informed agricultural decisions. Specifically, we find that households of PICSA-trained lead farmers are nearly four times more likely than their non-PICSA-trained counterparts to make use of seasonal forecasts to plan farm decisions. We observe almost a doubling of the likelihood of seasonal forecasts being used to choose crop variety and of the likelihood to adopt open-pollinated maize varieties. Maize yields for the households of trained lead farmers also increased.

The remainder of this article is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the PICSA approach and its implementation in Malawi. Section 4 presents the data and outcome variables, and outlines the identification strategy. Section 5 presents and discusses the results of the study. The final section concludes, highlighting lessons learned and policy recommendations.

2 | LITERATURE REVIEW

Systematic reviews on smallholder farming training find some evidence of the effectiveness of such interventions (Stewart et al., 2015; Waddington et al., 2014). For example, although evidence on the adoption of beneficial practices is inconclusive (Waddington et al., 2014), positive results for farmers' knowledge and food security are indicated (Stewart et al., 2015). Waddington et al. (2014) reviewed participants in farmer field schools, finding that these obtain around 13% higher yields than comparison groups (farmers not enrolled in farmer field schools), although much variation is seen across target populations and contexts. Most of these studies, however, are not backed by rigorous theory-based evaluations (Stewart et al., 2015; Waddington et al., 2014).

One model of extension services to farmers is based on a top-down, linear approach to knowledge uptake and use. A major shortcoming of this approach is that it fails to account for knowledge feedback from end-users, which undermines the effective translation of knowledge into action (Chapman & Schott, 2020; Guido et al., 2022). More recent approaches to agricultural extension have sought to overcome this shortcoming by exploiting synergies between experiential, technical, and social learning within farmer networks (Lubell et al., 2014). Integrating knowledge with what decision-makers value is especially important when dealing with complex issues such as farmer adaptation to climate risks (Bidwell et al., 2013). For example, Patt et al. (2005) suggest that there are high benefits from providing seasonal forecasts services to farmers through participatory methods. Their study piloted participatory workshops for farmers to promote the understanding and use of seasonal forecasts in four villages in Zimbabwe to find that the use of forecasts was associated with an average one-year increase in seasonal harvests of 9.4%. The PICSA approach uses participatory extension to understand farming systems and support the decision-making of smallholders.

A beneficiary assessment of PICSA in one district (not covered by our study) in Malawi and three districts in Tanzania (Statistics for Sustainable Development & Cramer-Njihia Consultants, 2017) reported that nearly all the farmers who attended PICSA training used the information provided on seasonal calendars and historical climate information for their farm decisions. In Balaka, Malawi, and Kondoa, Tanzania, PICSA training on crops and varieties was also used by nearly all respondents. Information on livestock and livelihood options was also reported to be widely used by farmers in Longido, Tanzania.

Overall, across the different countries where PICSA has been so far implemented, 52%–99% of trained farmers have reported changes to their crop, livestock, or livelihood activities as a result of PICSA (Clarkson et al., 2017; Clarkson et al., 2022; Dayamba et al., 2018). Complementary qualitative case studies have reported substantial improvements for PICSA-trained farmers in yields, profits, livelihoods, and food security (Clarkson et al., 2022).

However, most evaluations of climate-related interventions using participatory approaches to agriculture, awareness, and dissemination of information either take the form of beneficiary assessments, performance-monitoring evaluations, desk reviews, or case studies, which do not use a counterfactual evaluation design. Our contribution is to apply propensity score matching and regression adjustment methods to provide test causal estimates.

3 | THE PICSA INTERVENTION

PICSA is a training approach intended to empower farmers to make informed agricultural and livelihood decisions based on accurate, location-specific climate and weather information, using tools for participatory discussions. Training is delivered through a ToT in which extension officers are first trained and these then train farmer groups.

Training is divided into 12 steps, which ideally start at least eight to 12 weeks before the beginning of the rainy season.[1] The training guides farmers on topics such as awareness of climate change; identifying available opportunities to adapt crop, livestock, and livelihood activities; understanding seasonal and weather forecasts; and developing planning and decision-making tools for their activities.[2] Overall, PICSA uses participatory extension to understand farming systems and support the decision-making of smallholders. It uses historical and forecast-based climate data to highlight variability and risk such that smallholders can choose to adjust their practices as they deem fit.

In Malawi, PICSA targeted 14 districts identified as medium or highly food-insecure in the feasibility assessment for the M-CLIMES project (Government of Malawi, 2015).[3] Within each of the selected districts, an average of six extension planning areas (EPAs) were selected for the intervention based on, among other criteria, the proximity to weather stations to ensure the availability of reliable weather information. Within each EPA, only some sections (the administrative units under the EPA level) were selected for treatment, depending on the actual presence of agricultural extension development officers (AEDOs) in each section and the specific AEDO's motivation and expected ability regarding the objective of PICSA. Because of the strong participatory nature of PICSA, a high degree of spillover across lead farmers within and across EPAs in the PICSA districts was expected.[4] For the impact evaluation, the districts where PICSA was rolled out in 2018—Dedza, Chikwawa, Ntcheu, and Rumphi—were identified as the treatment districts. The districts of Dowa, Lilongwe, Mzimba, and Phalombe were identified as the control districts (see Figure A1 in the Appendix).[5]

PICSA farmer groups were established based on the already existing farmer groups within the Department of Agricultural Extension Services (DAES) and the National Smallholder Farmers Association of Malawi (NASFAM), following the “lead farmer” extension model employed by the Ministry of Agriculture and Food Security in Malawi.[6] Such lead farmers tend to be from the wealthier strata of rural communities with higher productivity, better social networks and a greater likelihood of adopting technology.

The intervention was set to follow the ToT approach designed by the UoR. In August 2018, PICSA experts from the UoR trained 92 AEDOs and 30 government and UNDP stakeholders. The 92 AEDOs previously trained by the UoR imparted a four-day training to an average of two groups of 25 to 40 lead farmers within their agricultural section of competence in the four treatment districts (henceforth called PICSA districts).

[1]Table A1 in the Appendix describes each of the 12 steps and their related timelines, as recommended by the PICSA manual developed by the Walker Institute at the UoR (Dorward et al., 2015).

[2]Malawi has a single rainy season lasting from October to May.

[3]The M-CLIMES project aims to increase the resilience of rural livelihoods to climate variability in Malawi through scaling up the use of modernized early warning systems (EWS) and climate information and is aligned with the priorities of the Government of Malawi on climate information and early warnings as set in the Malawi Growth and Development Strategy and the National Adaptation Programmes of Action (Government of Malawi, 2017; MMNRE, 2006). The M-CLIMES project stakeholders include the Department of Climate Change and Meteorological Services (DCCMS), the Department of Water Resources, the Department of Agricultural Extension Services (DAES), the Department of Fisheries, and the National Smallholder Farmers Association of Malawi (NASFAM).

[4]It would have been useful to collect data from a second control group comprising lead farmers in treatment districts who did not participate in PICSA trainings. Such a second control group could have allowed the assessment of potential spillover effects. Unfortunately, the limited budget did not allow the impact evaluation to include this additional comparison group.

[5]Because of the high degree of lead farmer spillover across EPAs, the control group had to be established in different districts. The high degree of interaction among smallholder farmers across these areas was confirmed by monitoring reports by the University of Reading.

[6]Swanson and Rajalati (2010) explain how agricultural extension “encompasses a wide range of communication and learning theories and activities (organized for the benefit of rural people) by professionals from different disciplines” (p. 176). Agricultural extension is often delivered by extension workers. The PICSA intervention was based on already existing farmer groups where lead farmers are responsible for training and passing on information to other farmers – referred to as contact farmers – in nearby villages.

Due to delays in training for the 2018 agricultural cycle in the PICSA districts, and capacity constraints, UNDP and the implementing partners shifted the training of contact farmers (farmers in nearby villages with whom lead farmers were expected to engage and train) to 2019, together with the lead farmer refresher training. However, training for contact farmers was later discarded. Instead, during the PICSA training, lead farmers were recommended to share their learning with their contact farmers. A UoR technical report indicates that, on average, trained lead farmers reported having shared PICSA tools and information with 17 farmers outside their households (Clarkson et al., 2020).

In September 2019, one year after the PICSA roll-out, AEDOs and lead farmers received refresher training. Refresher training consisted of summary revisions of specific PICSA topics that were selected based on feedback collected from PICSA lead farmers by UoR researchers during performance-monitoring fieldwork conducted in June 2019.

In October 2020, endline data collection took place in the 2018 PICSA districts (treatment districts) as well as the four control districts (Dowa, Lilongwe, Mzimba, and Phalombe) shortly before the PICSA roll-out in the control districts. Table A2 in the Appendix summarizes the timeline of data collection and implementation.

4 | DATA AND IDENTIFICATION STRATEGY

4.1 | Data and outcome variables

We aim to compare the household outcomes of lead farmers who participated in PICSA trainings with those of lead farmers that did not participate. We make use of primary data gathered via household surveys. At the onset of the 2018–2019 rainy season in October 2018 and before the PICSA trainings started, a baseline survey was conducted on a random sample of about 1,800 (roughly split between 30% lead and 70% contact farmer) households spread across four PICSA and four non-PICSA districts. The first consideration for selecting districts was to choose project-targeted districts and EPAs that had available weather and climate data from remote weather stations monitored by the Department of Climate Change and Meteorological Services. The data was key for generating climate information products (e.g. historical rainfall for a location) used during PICSA training. In addition, implementation partners DAES and NASFAM also prioritized districts which had already existing active lead farmers and farmer groups for ease of roll-out of the new PICSA training approach. The staggered approach was based on the annual financial resource allocation in that year. Therefore, treatment units were the first batch of districts exposed to PICSA while control units were from districts that had not been trained yet. Due to implementation challenges, only basic background information about the smallholders was retrieved at baseline.

Two years later, in October 2020, we tracked and resurveyed the same households to capture detailed information on their farming practices and other household outcomes of interest as well as baseline characteristics based on recall from interviewees.

We complement the survey data with GIS data on climatic and weather conditions. In particular, droughts and floods represent a major challenge (Government of Malawi, 2015). We retrieved temperature and precipitation from the CRU TS data set (AidData, n.d.; Climatic Research Unit, 2024), and we use information from the rainy seasons starting from October 2012 through to May 2018. We collected these data on the AidData portal (AidData, n.d.) and matched it to the latitude and longitude locations of our households and municipality boundaries in ArcGIS.

We focus on the effect of PICSA on its direct beneficiaries, the lead farmers who participated in the trainings and their respective households. After attrition, data cleaning, and matching with secondary data, the sample for the analysis amounts to 368 lead farmer households.[7] Of these, 154 households resided in a PICSA district and participated in at least one PICSA training since October 2018, while the remainder (214 households) resided in a district not yet exposed to the intervention by October 2020. We define treatment as residing in a PICSA district and having a lead farmer in the household who attended any PICSA training, from the first training rolled out in 2018 to the later refresher training rolled out in 2019. Conversely, control households reside in non-PICSA districts and hence, did not participate in PICSA trainings.[8] Table A3 in the Appendix displays baseline summary statistics of lead farmers and their households, separately by treatment status.

We consider four outcomes related to the 2019–2020 rainy season: (1) farming practices; (2) farming outputs; (3) livelihood security; and (4) food security. Below, we briefly describe the measurement of these variables. Table A4 in the Appendix describes the measurement of outcome variables in more detail.[9][10]

Farming practices. We capture whether households report having used seasonal forecasts to plan farm decisions as well as to make crop variety choices. Households were asked whether they made any changes to their crop or livestock activities (following Clarkson et al., 2020).[11]

Farming outputs. Households were asked which crops and, for each crop, which variety they cultivated, to recall how much harvest per cropped land they gained, and whether they sold it. We focused on maize, the crop most frequently grown in Malawi.

Livelihood security. This is measured as income from casual labour as a secondary source of income (known as *ganyu*). *Ganyu* covers a range of short-term rural labour relationships, the most common of which is piecework weeding or ridging on the fields of other smallholders or agricultural estates. After own-farm production, *ganyu* is the next most important source of livelihood and is a coping strategy for the poorest households in Malawi (Whiteside, 2000).

Food security. We use the Household Food Insecurity Access Score (HFIAS; see Coates et al., 2007) to measure food insecurity experienced during the last four weeks. In addition, we look at specific sub-indicators of the aggregate score capturing whether: (1) a household worried about not having enough food; (2) a household reported any member having eaten smaller meals than usual; or (3) a household eating fewer than three meals per day. Finally, we use the logarithm of food expenditures within the same reference period.[12]

Table A5 in the Appendix displays endline summary statistics of the outcome variables by treatment status.

[7]The overall attrition rate amounted to 8.8% (10% in the treatment group, 8% in the control group) and accounted for households that could not be traced at endline due to death, relocation, or sickness.

[8]To assess whether variation in precipitation correlated with the district-level selection of treatment and control groups, we checked for trends in precipitation for all eight districts as measured by weather stations. We found that all districts showed significantly less precipitation in the 2019–2020 season compared to averages from 2012–2018. These comparisons show a similar reduction across both treatment and control districts. In addition, when employing IPWRA, we include geo-climatic variables referring to the period after the baseline, which may correlate with the outcome variables and the treatment status. Specifically, we include the average temperature and rainfall during the rainy seasons from October 2018 to October 2020. Further, we include a measure of exposure (distance in kilometres) to a flood hazard in March 2019.

[9]Outcome variables of interest were not recorded in the baseline survey in 2018. The available baseline data includes only farmers' background characteristics. For this reason, baseline data are exclusively used to retrieve matching variables.

[10]As our study did not capture information on outcome variables at baseline, we checked how key variables varied across treatment and control districts outside the context of this intervention. Using the Fourth Integrated Household Survey 2016–2017 (NSO, 2017), we noted no significant disparities in pre-intervention outcomes related to food security and maize yields between treatment and control districts. Specifically, we examined three indicators: concern over household food sufficiency, instances of insufficient food within the past year, and maize harvest per hectare during the last rainy season. This last variable measured harvest during the last rainy season over all plots covering all types of maize: local, hybrid, composite/OPV, and hybrid recycled.

[11]The following changes in crop activities were considered: changed management of land, changed type or number of inputs, changed planting dates, decreased scale of a crop/variety, increased scale of a crop/variety, grew a new or a different crop/variety, changed irrigation schedule, and made investments in irrigation. The following changes in livestock activities were included: increased scale of a livestock activity, decreased scale of livestock activity, changed management of livestock activity, or tried a new breed of livestock.

[12]We smooth food-expenditures by taking the natural logarithm of their monetary values plus 1.

4.2 | Identification strategy

We estimate the effect on the outcomes of households of lead farmers that voluntarily participated in the training—that is, the intended beneficiaries that were "actually" treated,[13] known as "compliers". In other words, we estimate the "average treatment effect on the treated" (ATT). By focusing on the impact of PICSA on those who chose to adopt, we provide evidence for the direct benefits of the PICSA intervention on those who participated, which can inform decision-making about resource allocation and programme design. We attribute the estimated impact mainly to the PICSA intervention as other project activities that overlapped PICSA were still in progress at the time of endline survey.

Because of the non-random selection of participants in the intervention, a simple comparison of household outcomes between participants and non-participants would lead to a biased treatment effect estimation. We rely on a quasi-experimental methodology which employs matching and weighting estimators to control for selection bias due to observed characteristics.[14]

These estimators identify the causal effect of PICSA as the observed differences in outcomes between households of participant and non-participant lead farmers after the roll-out of the intervention while adjusting for other observed factors that may account for further differences between them that are not attributable to the intervention.[15] While we cannot rule out potential bias from unobserved factors, we attempt to address this with proxy variables captured in the endline survey. In the next section, we elaborate on the choice of control variables.

We use different matching and weighting estimators based on the propensity score to ensure our results are not driven by the choice of the method. We additionally make use of bias-adjustment regression to address residual covariate imbalance.[16]

The first estimator we employ is nearest-neighbour matching (NNM).[17] We match with replacement to increase the overall quality of the matching. One disadvantage of this estimator is that it may discard valuable information from potentially similar, yet unmatched, households from the control group. This makes NNM less efficient than other estimators and more likely to yield biased estimates.

An improvement to the loss of information from potentially good comparison households is the application of a radius around the propensity score for matching (Deheja & Wahaba, 1999, 2002; Rosenbaum & Rubin, 1985).[18] The second estimator we employ is the distance-weighted radius matching (DWRM) with bias-adjustment proposed by Lechner et al. (2011). The radius is defined as the 90th percentile of the distance obtained with nearest-neighbour matching, following Huber et al. (2014).

Different from standard radius matching, this estimator weights observations with the radius, and the weights are proportional to the absolute difference in the estimated propensity scores. This decreases variance in the estimation, as it assigns a smaller weight to control observations further away from the treatment observation for

[13] Our results are not representative of lead farmers who were selected to participate in the PICSA trainings but chose not to participate.

[14] The outcome variables are only observed post-treatment. This prevents us from employing alternative quasi-experimental identification strategies such as Difference in Differences.

[15] Identification relies on two key assumptions. First, the unconfoundness assumption, which states that, conditional on a vector of observed control variables X, the potential outcomes are independent of treatment status. In our setting, the unconfoundness assumption requires that there are no characteristics of lead farmer households that simultaneously affect any of the outcome variables as well as the probability of attending a PICSA training, after conditioning on X. Second, the common support assumption requires that the probability of attending a PICSA training is bounded away from zero and one. In other words, this assumption requires that households in the treatment group have a counterpart with a similar treatment probability in the control group.

[16] Regression adjustment follows the idea behind the doubly robust estimators (see, among others, Robins et al., 1995; Robins & Rotnitzky, 1995; van der Laan & Robins, 2003). Results are doubly robust in that it is sufficient that either the regression model or the propensity score model be correctly specified to ensure the consistency of the estimated treatment effects (Imbens & Wooldridge, 2009; Wooldridge, 2007).

[17] The matching procedure is relatively straightforward: each treatment household is paired with the single control household which is closest in terms of propensity score.

[18] Radius matching uses all available control observations within a predetermined radius. By doing so, it allows higher precision than NNM while reducing the risk of bad matches.

which the counterfactual is estimated. We use the procedure of Huber et al. (2014) to determine the radius. Remaining differences in observables after matching are controlled for in a regression model.[19] Hence, we refer to this estimator as distance-weighted radius matching with regression adjustment (DWRMRA).

An alternative estimation strategy to matching is to adjust for differences in the observed control variables X between treatment and control households by weighting the observed outcomes by the inverse of the propensity score. As the third estimator, we use the doubly robust inverse-probability-weighted estimator which combines inverse probability weighting (IPW) estimation with regression adjustment.[20] Sampling-based inference standard errors are used. For NNM, we report Abadie-Imbens standard errors (Abadie & Imbens, 2016). For the DWRMRA and inverse probability weighted regression adjustment (IPWRA) estimators, we report bootstrap standard errors with 1,000 replications.

5 | RESULTS

5.1 | Propensity score estimation

We estimate the probability that a lead farmer participated in at least one PICSA training using a probit model. Results are presented in Table 1. In the model, we only include characteristics reported for the baseline period, therefore unaffected by participation in PICSA trainings. The explanatory variables were chosen based on the literature on smallholder extension (Christoplos, 2010; Rivera, 2011) and are grouped into three sets: lead farmer characteristics, household characteristics, and local geo-climatic characteristics. Summary statistics of the explanatory variables for the treatment and control group are presented in Table A6 in the Appendix.

For the characteristics of the lead farmer, we first consider basic socio-demographics such as gender, age, and education. Next, we include characteristics specific to the extension work of the lead farmers. Because AEDOs purposively selected lead farmers for the PICSA trainings, we do not have a systematic list of criteria used for the selection. A key selection factor that emerged from qualitative interviews with AEDOs at baseline was the lead farmers' quality of extension work in terms of intrinsic motivation and connectedness with other farmers. We measure the quality of extension work along three dimensions: the number of supported contact farmers, the number of paid field visits, and the number of technologies promoted by the lead farmer. While the ratio of contact farmers per lead farmer could be an indication of connectedness, the number of field visits and the number of technologies promoted could serve as proxies for lead farmers' productivity and motivation.

These three dimensions of the quality of extension work are significantly correlated with the probability to participate in at least one PICSA training. The number of field contact farmers per lead farmer has a negative coefficient. The negative coefficient on the number of field visits indicates that lead farmers attending PICSA trainings were less likely to have paid visits to their contact farmers with respect to their peers in non-PICSA districts before the start of the intervention. The number of technologies promoted by lead farmers is positively related to the likelihood to attend PICSA trainings.

At household level, we control for whether the lead farmer is the head of the household, the number of household members and a set of characteristics proxying for household welfare. A substantial literature on participation in extension schemes finds that richer and better-networked smallholders benefit in general from better access to extension advice than poor smallholders in many developing countries (Christoplos, 2010; Haug, 1999; Rivera, 2011; Swanson & Rajalahti, 2010). Our approach to judging the welfare level of rural households is based

[19]The full sets of regression estimates are available on request.
[20]This estimator is also known as inverse probability weighting with regression adjustment (IPWRA) or "Wooldridge's doubly robust" estimator (Wooldridge, 2007).

TABLE 1 Propensity score estimation.

Variables	(1)
Age of lead farmer	−0.008
	(0.62)
Lead farmer is male ^	−0.236
	(0.72)
Lead farmer completed primary school ^	−0.879
	(0.98)
Lead farmer completed secondary school ^	−0.638
	(0.70)
Number of contact farmers followed by lead farmer	−0.022***
	(2.76)
Number of field visits to contact farmers by lead farmer	−0.047**
	(2.28)
Number of technologies promoted by lead farmer	0.322***
	(3.26)
Household keeps livestock ^	0.234
	(0.66)
Lead farmer is head of household ^	0.041
	(0.12)
Household size	0.031
	(0.44)
Access to mobile phone ^	−0.213
	(0.44)
Access to electricity ^	−0.306
	(0.86)
Iron sheet roofing ^	0.604*
	(1.82)
Brick/ concrete walls ^	−0.376
	(0.70)
Access to improved water source ^	−0.482
	(1.04)
Size of largest single crop area (acres)	0.067
	(0.81)
Village avg. distance to agricultural market (km)	0.019
	(1.19)
Municipality avg. temperature (C°), rainy season (October 2012–2018)	0.109
	(0.75)
Municipality avg. precipitation (mm), rainy season (October 2012–2018)	−0.032***
	(3.81)
Municipality avg. altitude (km)	−1.294**
	(2.26)

(Continues)

TABLE 1 (Continued)

Variables	(1)
Pseudo R-squared	0.23
LR Chi-squared p-value	0.00
Observations	348

Note: Probit estimation. The dependent variable is a binary indicator equal to 1 for lead farmers residing in PICSA districts, who attended at least one PICSA training; 0 for lead farmers in control district, and hence, were not exposed to the intervention. Standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%. Unless otherwise specified, all explanatory variables refer to October 2018. Variables marked with ^ are binary. The omitted categories for the roofing material are: grass, clay tiles. The omitted categories for the wall material are: mud, compacted earth, mud (unfired) bricks. The omitted categories for the education of the lead farmer are: never attended school, adult learning.

on assets owned or the type of house a household lives in.[21] We include a range of household-level variables that represent different asset categories: ownership of land and livestock, whether the family has electricity or not, dwelling characteristics such as iron sheet roofing and brick or concrete walls, and improved water source—based on the classification by the World Health Organization.[22]

Household access to a cell phone is included as it was a factor considered during the profiling of lead farmers prior to the selection into the intervention, as farmers were to receive seasonal and short-term forecasts by SMS.[23]

We also consider household distance to the agricultural market, as it affects costs of inputs and transport costs for farmers which are crucial to farmers' decisions.

We condition on local geo-climatic conditions experienced by the treatment and control groups. We use municipality-level data on temperature, rain patterns, and elevation. The latter two emerge as significant predictors and are negatively associated with the treatment probability.

The pseudo-R2 indicates that the matching variables can explain 23% of the variation in PICSA participation. The p-value of the LR Chi2 test shows that the explanatory variables are jointly significant.

5.2 | Common support and overlap in covariates distributions

Figure 1 presents the distributions of the propensity scores for lead farmers in the treatment (red colour) and control groups (blue colour). There is considerable overlap in the propensity scores between the two groups (common support). As expected, the distribution of the propensity scores of the treatment group is skewed in the opposite direction to that of the control group.

Observations that lie outside the common support are trimmed from the sample. Overall, 36 observations from the treatment group and three observations from the control group are trimmed, amounting to about 10%

[21]Studies that illustrate this approach in combination with a range of statistical methods include Mahmud and Prowse (2012), Sakketa and Prowse (2018), Jensen et al. (2019).

[22]As defined by the Joint WHO & UNICEF Monitoring Programme (JMP), an improved drinking-water source is one that by its construction adequately protects the source from outside contamination. These include piped water connection into dwelling, yard, or plot; public tap or standpipe; tube well or borehole; protected dug well; protected spring.

[23]The proportion of PICSA lead farmers that reportedly received weather forecasts and advisory agricultural advisory via SMS from any source was quite low (14.4%, i.e. 35 lead farmers, in treatment; and 5%, i.e. 12 lead farmers, in control districts). Discussions with the project staff at the time of the endline survey revealed that the implementing partner was still working on profiling lead farmers in most districts. As a result, most lead farmers' phones were not yet connected to the SMS service. Because of this, most lead farmers still mainly accessed weather forecasts through their extension workers who were receiving the SMS from the Department of Climate Change Management Services via their phones.

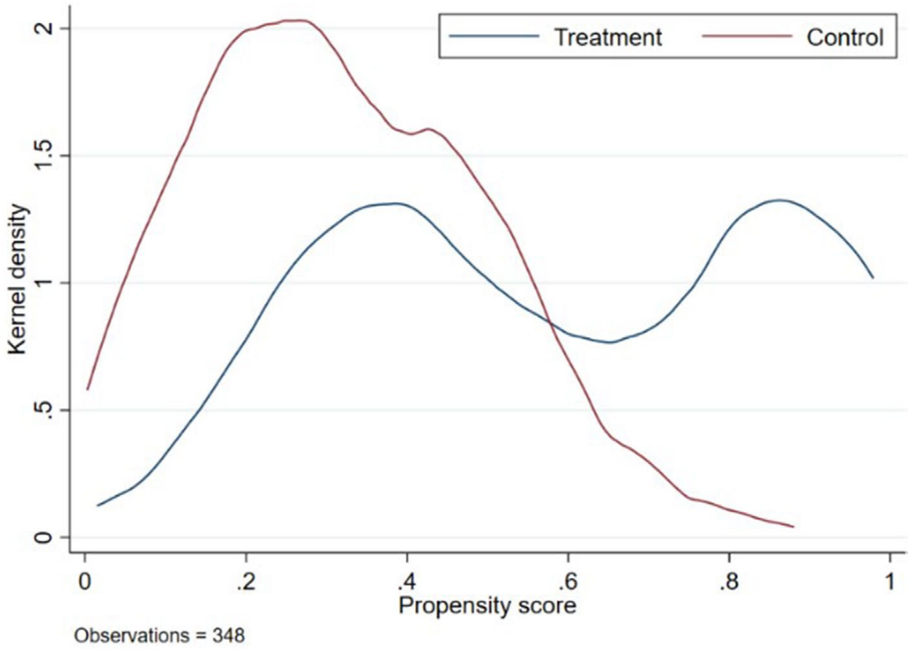

FIGURE 1 Propensity score distribution.

of the sample for which the propensity score was estimated. Table A7 in the Appendix compares the sample of treatment observations that are dropped to the remaining treatment observations used for the final analysis for the treatment group. Lead farmers in treatment households in the final sample paid a relatively higher number of visits to their contact farmers but promote a lower number of technologies on average than trimmed households. They also appear less wealthy than the trimmed households, who are more likely to have brick or concrete walls and to possess larger crop land than the rest. Finally, they live in municipalities that are on average more elevated and have experienced warmer rainy seasons with lower precipitation in the years preceding the intervention. For the analysis, we only use observations within the area of common support.

Balance for each covariate is measured by the standardized bias (Rosenbaum & Rubin, 1985).[24] As a rule of thumb, a reduction of the standardized bias below one quarter is considered sufficient. Table A8 in the Appendix shows balance improvements comparing the standardized bias in the treatment versus the control group in the raw sample versus after matching or weighting. Figure A2 in the Appendix shows graphically the standardized differences after the application of the algorithms.

IPW yields the best balance, with only one variable associated with a standardized bias above 0.25 as compared to three for the other two algorithms. Regression adjustment helps to correct for remaining differences after IPW and DWRM. DWRMRA uses the matching variables weights obtained from matching for the while IPWRA allows to include more variables than those used for matching.

When employing IPWRA, we include the matching variables as well as geo-climatic variables referring to the period after the baseline, which may correlate with the outcome variables and the treatment status. Specifically, we include average temperature and rainfall from October 2018 to October 2020. These variables are retrieved from the AidData.org portal (AidData, n.d.) as the respective matching variables for the pre-treatment period (see Section 4). Additionally, we include a measure of exposure (distance in kilometres) to a flood hazard related to Cyclone Idai, which hit Malawi in March 2019. The flood exposure data was retrieved from Copernicus, the

[24]The standardized bias is given by the difference of the group means normalized by the square root of the sum of the group variances.

Emergency Management Service of the European Union (Copernicus, 2019). Summary statistics of these variables for the treatment and control group are presented in Table A9 in the appendices. Households in the treatment group were, on average, likely to be exposed to slightly lower temperatures, received slightly higher levels of precipitation, and lived further away from the area directly affected by the 2019 Cyclone Idai flood (all significant at the 1% level).

5.3 | Treatment effects

5.3.1 | Farming practices

The estimated treatment effects are presented in Table 2. The estimates suggest that PICSA led to positive impacts on lead farmers in use of seasonal forecasts to plan farm decisions, use of seasonal forecasts to make crop variety choices, and led to changes in crop activities on the farm.

We detect a robust positive treatment effect, ranging between 7.2 to 8.4 percentage points across all the estimation methods (control group mean: 2.1%) on the use of seasonal forecasts to plan farm decisions. PICSA increased use of seasonal forecasts by a factor of around four.

PICSA doubled the likelihood of using seasonal forecasts by lead farmers to make crop variety choices (bringing this to around one third of smallholders). The estimates range from 17.6 to 22.3 percentage points (control group mean: 18.1%). Similarly, the likelihood to change crop activities increased by 21.8 to 36.2 percentage points (control group mean: 31.6%). These findings highlighted broad and high levels of adoption of PICSA by treated farmers.

No significant impacts on changes in livestock activities were seen. It may be that most farmers received more detailed information from PICSA about changes in cropping than about livestock (as the majority of households earn more of their income from crops rather than from livestock, both in our survey and in Malawi in general).

5.3.2 | Farming outputs

We do not find any evidence that PICSA farmers increased the number of crops grown. Yet estimates suggest differences in the choice of maize varieties by lead farmers. Farmers that participated in PICSA training are significantly more likely to have planted open-pollinated maize varieties (7.6 to 7.9 percentage points; control group mean: 4.7%): an increase in the adoption of open-pollinated varieties (OPVs) of maize and a sizeable shift from local maize varieties. This effect is significant for two estimation methods.

Smallholders in Malawi have continued to grow local maize varieties as local varieties tend to require lower fertilizer requirements for a reasonable yield, and, importantly, fewer chemicals post-harvest as maize kernels tend to be harder and suffer fewer post-harvest losses (from, for example, weevils). Preference for local maize has however limited crop diversification on smallholders' small plots.

PICSA may be a suitable channel to support agricultural intensification and deliver climate information, supporting smallholder moves towards varieties of maize, including OPV, which offer higher yields than local maize and which better withstand drought (Katengeza & Holden, 2021; see also Prowse & Grassin, 2020).

Farmers in the treatment group reported significantly higher maize yields compared to their peers in the control group. The estimated increases in maize yields range between 823.6 kg/ha and 1,176.2 kg/ha. This effect size is substantial when compared to the control group mean (1979.1 kg/ha), representing an increase of 42%–59%. Smallholder yields of maize in Malawi tend to range between 1,400 kg/ha and 2,400 kg/ha. An increase of this magnitude reinforces the need for additional and wider impact evaluations of PICSA interventions to check effectiveness across

TABLE 2 ATT estimates.

Dependent variables	NNM	IPWRA	DWRM	Observations	Control group mean
Use of seasonal forecasts to plan farm decisions	0.084**	0.072***	0.074***	312	0.021
	(0.038)	(0.028)	(0.026)		
Use of seasonal forecasts to make crop variety decisions	0.176**	0.223***	0.179***	312	0.181
	(0.088)	(0.070)	(0.051)		
Any changes to crop activities	0.218**	0.357***	0.362***	312	0.316
	(0.091)	(0.098)	(0.055)		
Any changes to livestock activities	0.000	−0.023	−0.039	312	0.145
	(0.076)	(0.083)	(0.059)		
Number of crops grown	0.202	0.203	0.067	312	2.777
	(0.233)	(0.225)	(0.147)		
Cropped maize	−0.008	−0.030	−0.032	312	0.990
	(0.038)	(0.022)	(0.019)		
Cropped local maize variety	−0.134*	−0.105	−0.166***	312	0.218
	(0.073)	(0.076)	(0.060)		
Cropped hybrid maize variety	0.092	0.063	0.077	312	0.782
	(0.071)	(0.072)	(0.061)		
Cropped OPV maize variety	0.076**	0.048	0.079***	312	0.047
	(0.036)	(0.037)	(0.028)		
Maize yield	1176.192***	886.726**	823.611**	292	1979.112
	(423.539)	(439.379)	(352.352)		
Sold maize	0.044	0.094	0.101*	305	0.346
	(0.092)	(0.098)	(0.058)		
Ganyu income source	−0.151*	−0.031	−0.087	312	0.269
	(0.081)	(0.074)	(0.061)		
HFIAS (0–27)	−3.983***	−2.462*	−2.157*	312	6.710
	(1.519)	(1.282)	(1.254)		
Worried about food shortage	−0.176**	−0.078	−0.105	312	0.451
	(0.087)	(0.101)	(0.069)		
Smaller meals than usual	−0.134	−0.180*	−0.131*	312	0.440
	(0.087)	(0.092)	(0.069)		
Fewer than three meals per day	−0.185**	−0.141	−0.134*	312	0.440
	(0.092)	(0.100)	(0.069)		
Ln of food expenditures	0.123	0.087	−0.080	312	9.174
	(0.280)	(0.192)	(0.157)		

Sampling-based inference standard errors in parentheses. Significance levels: *** 1%, ** 5%, * 10%.
Note: The number of observations is slightly lower for maize yields and maize sales.

contexts and crops. The wider literature on the effectiveness of smallholder extension interventions such as farmer field schools offers much lower yield increases—for example, the evidence from a recent systematic review reports an average impact of 13% on yields (Waddington et al., 2014). This is the benchmark against which an aggregated effect size from PICSA interventions across contexts should be compared.

5.3.3 | Livelihood security

Working on other farms (*ganyu*) is an indication of poverty in Malawi. We observe a statistically significant (only at the 10% level) reduction in participation by lead farmers (−15.1 percentage points; control group mean: 26.9%) only for the NNM estimation.

5.3.4 | Food security

We find some evidence of improved food security for lead farmers. We find a substantial reduction in the HFIAS score (−2.16 to −4; control group mean 6.7) significant across all three estimation methods. Among treated farmers, across one or more estimation methods, worries about food shortages were lower by 17.6 percentage points (control group mean 0.45); households eating smaller meals than usual in the preceding four weeks were lower (−0.13 to −0.18; control group mean 0.44); and households eating less than three meals a day were fewer (−0.13 to −0.19; control group mean 0.44). No significant effect was found on food expenditure.

Our findings on food security suggest PICSA delivered benefits with potential longer-term benefits for nutrition (Table 2).

6 | CONCLUSIONS

The productivity of smallholder farmers in developing countries is increasingly vulnerable to climate variability and climate change. Yet evidence from rigorous, empirically based evaluations of climate-related interventions, including mitigation and adaptation, is far from plentiful.

With that in mind, we investigate the causal impact effects of PICSA, a training intervention to empower farmers to make informed agricultural and livelihood decisions based on accurate, location-specific climate and weather information, and to use tools for participatory discussions. Training was delivered through a ToT approach, where extension officers were first trained and were then responsible for leading training sessions of lead farmers. The PICSA intervention accords with national adaptation and development priorities.

We employ propensity-score-based estimations and regression adjustment methods on primary data gathered before and after the rollout of the PICSA training to identify the causal effect of PICSA on farmer household outcomes while controlling for observed characteristics. Our results suggest that PICSA translated into higher use of seasonal forecasts for farming decisions. Treated farm households are more likely to implement changes in crop activities, make more use of OPV maize varieties, and report increased maize yields compared to their peers in the control group. We find some evidence, albeit not robust, of a reduction in *ganyu* income and improved food security.

While we find evidence of PICSA benefits, we do not know whether these effects will be sustained in the long run or meet the M-CLIMES project goal of enhanced farmers' resilience against climate change. A longer evaluation timeframe and a more complex approach would be necessary to assess such impacts.

Our results apply to lead farmers; but most farmers in Malawi are contact farmers. PICSA in Malawi did not directly involve contact farmers during training owing to implementation challenges, including capacity constraints for the implementing agencies. The assumption that lead farmers would understand the PICSA content from AEDOs and pass it on to contact farmers is ambitious. When communication channels become longer, critical information is lost as it moves from one person to another.

The following two policy suggestions to improve the design and implementation of PICSA and similar interventions can be inferred. First, PICSA is a short-term intervention and it is not clear if it will be sustained. Refresher meetings of a similar nature should be held regularly to enhance learning, mobilize knowledge exchange between lead and contact farmers, and improve their decision-making.

Second, owing to the limited number of AEDOs across the country, complementary training could be given. Training lead farmers directly may be more effective and would reduce the length of the knowledge exchange chain, reducing loss of information and potentially reaching a larger group of contact farmers.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ETHICS STATEMENT

The ethics of data collection and analysis were approved by the Ministry of Agriculture, Government of Malawi. Persons from whom data were collected gave their free, prior and informed consent. Their data has been used anonymously.

DISCLOSURE STATEMENT

The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

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APPENDIX A

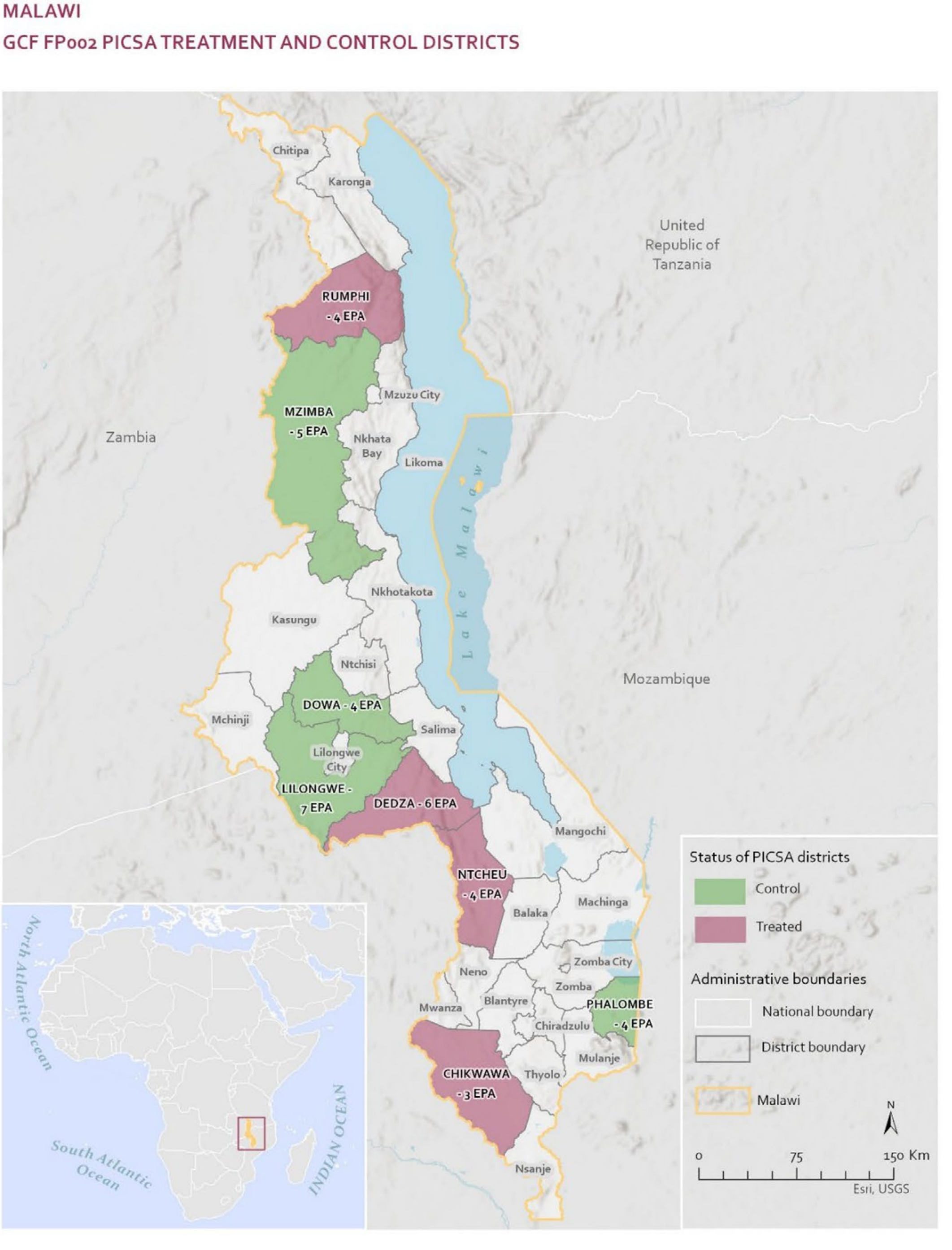

FIGURE A1 Map of Malawi showing PICSA treatment and control districts where the endline evaluation was conducted.

Source: Project data, UNDP Malawi; national boundaries, global administrative boundaries data set;Malawi district boundaries, United Nations Office for the Coordination of Humanitarian Affairs; physical data, ESRI, USGS.

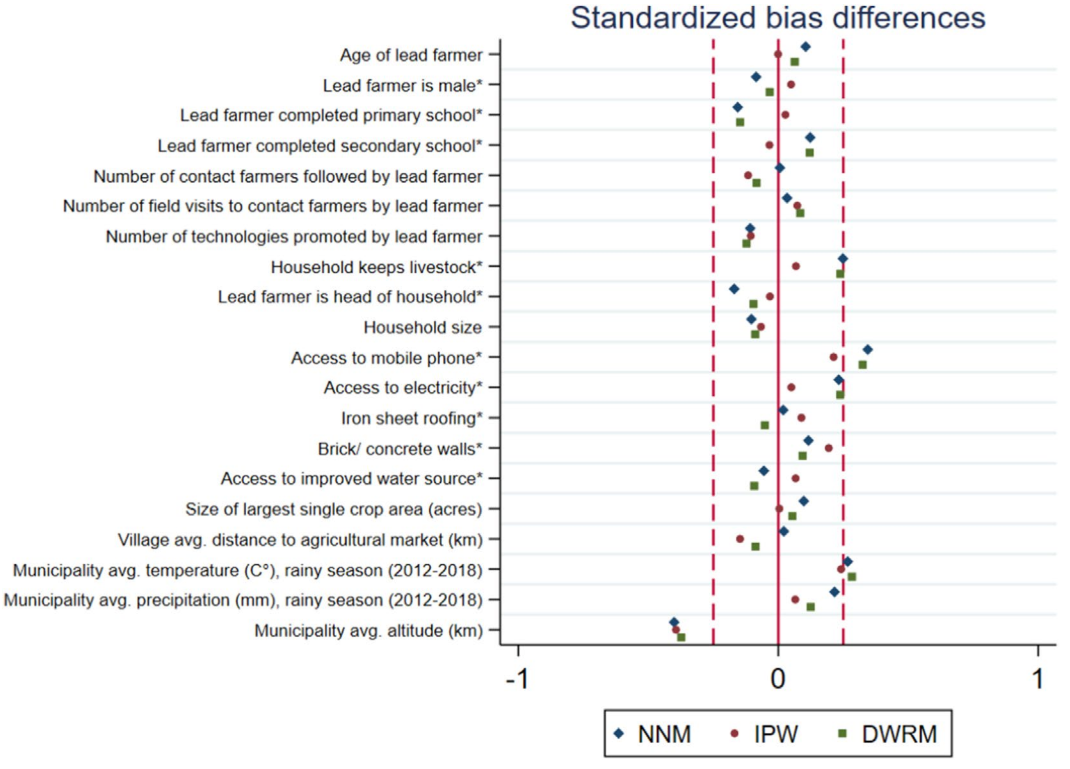

FIGURE A2 Standardized bias differences after matching or weighting.

TABLE A1 PICSA training steps.

Step	Description	Ideal timeline
A	What does the farmer currently do?	Long (at least 8–12 weeks) before the rainy season
B	Is the climate changing?	
C	What are the opportunities and risks?	
D	What are the options for the farmer?	
E	Options by context	
F	Compare different options and plans	
G	The farmer decides	
H	Seasonal forecasts	When the seasonal forecast is available
I	Identify and select possible responses to the forecast	
J	Short-term forecasts and warnings	Just before and during the growing season
K	Identify and select possible responses to the forecast	
L	Learn from the experience and improve the process	At end of the rainy season

Source: Dorward et al. (2015).

TABLE A2 Timeline of intervention and data collection for evaluation.

Timeline	Activity	Remarks
Before 2018	14 districts identified by UNDP as medium or highly food-insecure for project implementation	
Winter season		
June 2018	Profiling data collection to gather interest for tailored messages	308 AEDOs and 4,718 lead farmers
August 2018	92 AEDOs trained by UoR	
October 2018	Baseline data collected	Total sample size: 1,802
Harvesting ends and the rainy season starts		
October 2018	Two groups of 25–40 lead farmers trained by AEDOs in each of the first four districts	8–10 weeks before the start of the rainy season
The rainy season ends and the winter season starts		
June 2019	UoR evaluation of PICSA: a random sample of lead farmers	On average, each lead farmer shared information with 17 contact farmers
September 2019	AEDOs and lead farmers received refresher training sessions, by UoR (1 day) and AEDOs (2 days)	
October 2020	Endline data collected	Total sample size: 1,644 (merged with baseline: 1,586)
November 2020	PICSA rolled out in the final four districts	Served as a control group
Harvesting ends and the rainy season starts		

Source: Own representation based on information provided by UNDP.

TABLE A3 Characteristics of the sample at baseline.

	Control Mean	Treatment Mean	Mean Diff. (2–1)	Obs.
Lead farmer is head of household*	0.74	0.69	−0.05 (0.05)	368
Household size	5.85	5.89	0.04 (0.21)	368
Access to mobile phone*	0.92	0.90	−0.02 (0.03)	368
Access to electricity*	0.83	0.80	−0.03 (0.04)	368
Iron sheet roofing*	0.68	0.76	0.08 (0.05)	368
Brick/concrete walls*	0.92	0.94	0.02 (0.03)	368
Access to improved water source*	0.92	0.90	−0.02 (0.03)	368
Access to radio*	0.87	0.88	0.01 (0.04)	368
Size of largest single crop area (acres)	2.17	2.51	0.34 (0.18)	368
Number of crop varieties grown	2.55	2.86	0.32* (0.14)	368
Income from crop production, rainy season 2017/2018	219648.98	216209.57	−3439.41 (35793.65)	338
Income from livestock production, rainy season 2017/2018	48483.49	64988.24	16504.75 (13321.67)	211
Received any seasonal rainfall warning in last three years (2016–2018)	0.01	0.01	−0.01 (0.01)	368
Experienced any natural hazard in last three years (2016–2018)	0.99	1.00	0.01 (0.01)	368
Village avg. distance to agricultural market (km)	5.83	6.47	0.63 (0.94)	368
Village avg. distance from main road is 1 km or less*	0.41	0.31	−0.10* (0.05)	368
Municipality avg. temperature (C°), rainy season (2012–2018)	22.39	23.65	1.25*** (0.20)	368
Municipality avg. precipitation (mm), rainy season (October 2012–2018)	123.37	111.06	−12.31*** (1.89)	368
Municipality avg. altitude (km)	1.10	0.84	−0.26*** (0.05)	368

Unless otherwise specified, all variables refer to October 2018. Variables marked with asterisk are binary. Significance levels: *** 1%, ** 5%, * 10%. The number of observations reported is the sum of the sample size of the two groups considered. Standard errors for the mean differences between the two groups are in parenthesis. The number of contact farmers of lead farmer and the number of field visits of lead farmer are winsorized at the ninth percentile. The size of the largest single crop area is winsorized at the first and ninth percentile. Crop income and livestock income in the rainy season 2017/2018 are winsorized at the 99th percentile.

TABLE A4 Outcome measurement.

Outcome	Measurement
Use of seasonal forecasts to plan farm decisions	1 if a lead farmer household reported using seasonal forecast to plan farm decisions (such as the timing and style of land management techniques such as ridging, bunding, weeding as well as input use) in the 2019/2020 rainy season, 0 otherwise
Use of seasonal forecasts to make crop variety choices	1 if a lead farmer household reported using seasonal forecast to choose crop varieties to plant in the 2019/2020 rainy season, 0 otherwise
Made changes to crop activities	1 if a lead farmer made changes to crop activities in the 2019/2020 rainy season, 0 otherwise
Number of crops grown	Number of crops grown by a lead farmer household in the last rainy season (2019/2020)
Cropped maize	1 if a lead farmer household cultivated maize in the 2019/2020 rainy season, 0 otherwise.
Cropped local maize variety	1 if a lead farmer household cultivated a local variety of maize in the 2019/2020 rainy season, 0 otherwise
Cropped OPV maize variety	1 if a lead farmer household cultivated an open-pollinated variety (OPV) of maize in the 2019/2020 rainy season, 0 otherwise
Cropped hybrid maize variety	1 if a lead farmer household cultivated a hybrid variety of maize in the 2019/2020 rainy season, 0 otherwise
Maize yield	Yield is quantity harvested over cropped land size (kg/ha) for maize in last rainy season 2019/2020. The variables quantity harvested and cropped land size were winsorized at the first and ninth percentile.
Sold maize	1 if a lead farmer household cultivated maize in the 2019/2020 rainy season, 0 otherwise.
Made changes to livestock activities	1 if a lead farmer household made changes to livestock activities in the 2019 rainy season
Ganyu income source	1 if a lead farmer household earned income from casual labour in the last rainy season (2019/2020), 0 otherwise
HFIAS	Household Food Insecurity Access Score, developed by USAID, based on nine questions relating three domains of food insecurity experienced in the last four weeks: (1) uncertainty about the household food supply; (2) insufficient quality of food in terms of variety and preferences; (3) insufficient food intake and its physical consequences. The nine questions include: (1) Worry that their household would not have enough food; (2) Not able to eat the kinds of foods preferred because of lack of resources; (3) Eat a limited variety of foods due to a lack of resources; (4) Eat some foods that they really did not want to eat because of lack of resources to obtain other types of food; (5) Eat a smaller meal at breakfast, lunch, or dinner than they felt they needed because there was not enough food; (6) Eat less than three meals in a day because there was not enough food; (7) No food to eat of any kind and no way to get more through purchases, your garden, or farm, or from storage; (8) Go to sleep at night hungry because there was not enough food; (9) Go a whole day and night without eating anything because there was not enough food. Within each of these questions, the households report the frequency of occurrence. See Coates et al. (2007) for a detailed explanation of the HFIAS score construction. The aggregate HFIAS score takes values from 0 to 27. The lower the score, the better the food security.
Worried about food shortage	1 if a lead farmer household worried about not having enough food during the last four weeks, 0 otherwise

(Continues)

TABLE A4 (Continued)

Outcome	Measurement
Smaller meals than needed	1 if a lead farmer household reported about any member who ever had smaller meals than needed in the last four weeks, 0 otherwise
Fewer than three meals per day	1 if a lead farmer household reported about any member who ever ate fewer than three meals per day in the last four weeks, 0 otherwise
Ln of food expenditures	Natural logarithm of total household food expenditures during the last four weeks. We smooth food expenditure by taking the natural logarithm of their monetary values plus 1.

TABLE A5 Summary statistics of outcome variables at endline.

	Control Mean	Treatment Mean	Mean Diff. (2–1)	Obs.
Use of seasonal forecasts to plan farm decisions*	0.02	0.10	0.09** (0.03)	368
Use of seasonal forecasts to make crop variety choices*	0.19	0.38	0.19*** (0.05)	368
Made changes to crop activities*	0.33	0.62	0.30*** (0.05)	368
Number of crops grown	2.73	2.96	0.23 (0.13)	368
Cropped maize	0.99	0.92	−0.07** (0.02)	368
Cropped local maize variety	0.22	0.11	−0.11** (0.04)	368
Cropped OPV maize variety	0.78	0.81	0.03 (0.04)	368
Cropped hybrid maize variety	0.05	0.06	0.01 (0.03)	368
Maize yield	159.75	196.29	36.54 (25.19)	337
Sold maize	0.35	0.53	0.17** (0.05)	354
Made changes to livestock activities*	0.15	0.21	0.06 (0.04)	368
Casual labour/*ganyu* income source of livelihood	0.29	0.19	−0.11* (0.04)	368
Worried about food shortage*	6.62	4.46	−2.16** (0.75)	368
HFIAS (0–27)	0.46	0.29	−0.17*** (0.05)	368
Smaller meals than needed* (last four weeks)	0.43	0.25	−0.18*** (0.05)	368
Fewer than three meals per day* (last four weeks)	0.43	0.29	−0.15** (0.05)	368
Ln of food expenditure (last four weeks)	9.15	9.19	0.04 (0.13)	368

Unless otherwise specified, all variables refer to the rainy season 2019/2020. Variables marked with asterisk are binary. Significance levels: *** 1%, ** 5%, * 10%. The number of observations reported is the sum of the sample size of the two groups considered. Standard errors for the mean differences between the two groups are in parenthesis. Maize yield is winsorized at the first and ninth percentile.

TABLE A6 Summary statistics of variables included in the propensity score model.

	Control Mean	Treatment Mean	Mean Diff. (2–1)	Obs.
Age of lead farmer	45.58	46.00	0.42 (1.18)	365
Lead farmer is male*	0.62	0.56	−0.06 (0.05)	362
Lead farmer completed primary school*	0.60	0.59	−0.02 (0.05)	363
Lead farmer completed secondary school*	0.38	0.38	0.00 (0.05)	363
Number of contact farmers followed by lead farmer	29.37	17.19	−12.18*** (2.88)	356
Number of field visits to contact farmers by lead farmer	7.60	5.69	−1.91* (0.78)	356
Number of technologies promoted by lead farmer	2.07	2.81	0.75*** (0.15)	368
Household keeps livestock*	0.79	0.86	0.06 (0.04)	368
Lead farmer is head of household*	0.74	0.69	−0.05 (0.05)	368
Household size	5.85	5.89	0.04 (0.21)	368
Access to mobile phone*	0.92	0.90	−0.02 (0.03)	368
Access to electricity*	0.83	0.80	−0.03 (0.04)	368
Iron sheet roofing*	0.68	0.76	0.08 (0.05)	368
Brick/concrete walls*	0.92	0.94	0.02 (0.03)	368
Access to improved water source*	0.92	0.90	−0.02 (0.03)	368
Size of largest single crop area (acres)	2.17	2.51	0.34 (0.18)	368
Village avg. distance to agricultural market (km)	5.83	6.47	0.63 (0.94)	368
Municipality avg. temperature (C°), rainy season (October 2012–2018)	22.39	23.65	1.25*** (0.20)	368
Municipality avg. precipitation (mm), rainy season (October 2012–2018)	123.37	111.06	−12.31*** (1.89)	368
Municipality avg. altitude (km)	1.10	0.84	−0.26*** (0.05)	368

Unless otherwise specified, all variables refer to October 2018. Variables marked with asterisk are binary. Significance levels: *** 1%, ** 5%, * 10%. The number of observations reported is the sum of the sample size of the two groups considered. Standard errors for the mean differences between the two groups are in parenthesis.

TABLE A7 Comparison of dropped versus final treatment group sample.

	Dropped Mean	Final Mean	Mean Diff. (2–1)
Age of lead farmer	47.45	45.66	−1.80 (2.13)
Lead farmer is male*	0.55	0.57	0.03 (0.10)
Lead farmer completed primary school*	0.58	0.59	0.01 (0.10)
Lead farmer completed secondary school*	0.36	0.39	0.02 (0.10)
Number of contact farmers followed by lead farmer	13.03	18.36	5.33* (2.57)
Number of field visits to contact farmers by lead farmer	4.27	6.04	1.77 (1.08)
Number of technologies promoted by lead farmer	3.58	2.61	−0.96*** (0.24)
Household keeps livestock*	0.91	0.84	−0.07 (0.06)
Lead farmer is head of household*	0.73	0.69	−0.04 (0.09)
Household size	5.79	5.93	0.14 (0.40)
Access to mobile phone*	0.94	0.90	−0.04 (0.05)
Access to electricity*	0.79	0.80	0.01 (0.08)
Iron sheet roofing*	0.85	0.73	−0.12 (0.08)
Brick/concrete walls*	1.00	0.92	−0.08** (0.02)
Access to improved water source*	0.91	0.89	−0.02 (0.06)
Size of largest single crop area (acres)	3.16	2.34	−0.82* (0.38)
Village avg. distance to agricultural market (km)	6.17	6.52	0.35 (1.46)
Municipality avg. temperature (C°), rainy season (October 2012–2018)	26.78	22.78	−4.00*** (0.20)
Municipality avg. precipitation (mm), rainy season (October 2012–2018)	95.18	115.30	20.13*** (1.23)
Municipality avg. altitude (km)	0.16	1.02	0.86*** (0.04)
Observations	152		

Dropped stands for the group of treatment observations that are trimmed because they fall outside of the area of common support. Final stands for the group of treatment observations remaining after trimming and constitutes the sample of analysis. Overall, 36 observations from the treatment group. Significance levels: *** 1%, ** 5%, * 10%. The number of observations reported is the sum of the sample size of the two groups considered. Standard errors for the mean differences between the two groups are in parenthesis.

TABLE A8 Standardized bias differences in the sample before versus after matching or weighting.

Variables	Raw	NNM	IPW	DWRM
Age of lead farmer	−0.028	0.105	−0.001	0.063
Lead farmer is male*	−0.092	−0.085	0.049	−0.033
Lead farmer completed primary school*	−0.058	−0.156	0.027	−0.147
Lead farmer completed secondary school*	0.038	0.122	−0.034	0.121
Number of contact farmers followed by lead farmer	−0.348	0.006	−0.116	−0.084
Number of field visits to contact farmers by lead farmer	−0.186	0.034	0.073	0.084
Number of technologies promoted by lead farmer	0.300	−0.108	−0.106	−0.122
Household keeps livestock*	0.071	0.248	0.068	0.239
Lead farmer is head of household*	−0.127	−0.170	−0.032	−0.096
Household size	0.057	−0.103	−0.067	−0.089
Access to mobile phone*	−0.081	0.344	0.213	0.325
Access to electricity*	−0.106	0.233	0.050	0.238
Iron sheet roofing*	0.059	0.019	0.089	−0.051
Brick/concrete walls*	−0.012	0.116	0.194	0.094
Access to improved water source*	−0.148	−0.056	0.067	−0.093
Size of largest single crop area (acres)	0.078	0.098	0.004	0.054
Village avg. distance to agricultural market (km)	0.070	0.021	−0.147	−0.088
Municipality avg. temperature (C°), rainy season (October 2012–2018)	0.266	0.267	0.241	0.283
Municipality avg. precipitation (mm), rainy season (October 2012–2018)	−0.439	0.216	0.065	0.125
Municipality avg. altitude (km)	−0.213	−0.400	−0.394	−0.373

Raw stands for the full sample. NNM, IPW and DWRM indicate the samples after using each respective algorithm.

TABLE A9 Summary statistics of geo-climatic variables included in the regression adjustment.

	Control Mean	Treatment Mean	Mean Diff. (2–1)	Obs.
Municipality avg. temperature (C°), rainy season (October 2018–2020)	22.72	21.53	−1.19*** (0.20)	368
Municipality avg. precipitation (mm), rainy season (October 2018–2020)	92.22	104.89	12.67*** (1.72)	368
Household distance (km) from 2019 Cyclone Idai flood	144.69	192.89	48.20*** (13.64)	368

Significance levels: *** 1%, ** 5%, * 10%. The number of observations reported is the sum of the sample size of the two groups considered. Standard errors for the mean differences between the two groups are in parenthesis.