LORTA

Impact evaluation report for FP002

Scaling up the use of Modernized Climate Information and Early Warning Systems in Malawi

April 2022

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Learning-Oriented Real-Time Impact Assessment Programme (LORTA)

Impact evaluation report for FP002 - Scaling Up the Use of Modernized Climate Information and Early Warning Systems in Malawi

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PREFACE

In 2018, the Independent Evaluation Unit initiated the Learning-Oriented Real-Time Impact Assessment (LORTA) programme, within which it collaborates with the Center for Evaluation and Development (C4ED), project teams funded by the Green Climate Fund (GCF), local evaluation teams and academics. The LORTA programme incorporates state-of-the-art approaches for impact evaluations to measure results and raise awareness about the effectiveness and efficiency of GCF projects. This impact evaluation of one component of FP002 - Scaling Up the Use of Modernized Climate Information and Early Warning Systems in Malawi, specifically the Participatory Integrated Climate Services for Agriculture (PICSA) component, was designed to align with the LORTA approach for measuring causal impacts.

The LORTA programme has a twofold aim: (a) to embed real-time impact evaluations into funded projects so GCF project task managers can quickly access accurate data on the project's quality of implementation and likelihood of impact; and (b) to build capacity within projects to design high-quality data sets for overall impact measurement. The purpose of the impact evaluations is to measure the change in key result areas of the GCF that can be attributed to project activities. The LORTA programme is informing on the impacts of GCF projects and helps GCF projects track implementation fidelity.

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The team extends their gratitude to the national and district staff from the Department of Agricultural Extension Services and the National Smallholder Farmers' Association of Malawi in the Rumphi, Mzimba, Dowa, Lilongwe, Dedza, Ntcheu, Chikwawa and Phalombe districts for their guidance and support during data collection. The study would not have been successful without the cooperation and support of all agricultural extension officers and field officers in all extension planning areas where the study was conducted. Finally, we are indebted to the lead farmers and respective contact farmers who provided valuable information used in this report.

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ABBREVIATIONS

AEDO	Agricultural extension development officer
C4ED	Center for Evaluation and Development
CF	Contact farmer
CIE	Centre for Independent Evaluation
DAES	Department of Agricultural Extension Services
DCCMS	Department of Climate Change Management Services
DoDMA	Department of Disaster Management Affairs
EPA	Extension planning areas
EQ	Evaluation question
EWS	Early warning system
GCF	Green Climate Fund
ICC	Intra-cluster correlation
IE	Impact evaluation
IEU	Independent Evaluation Unit
LF	Lead farmer
LORTA	Learning-Oriented Real-Time Impact Assessment
M-CLIMES	Modernized Climate Information and Early Warning Systems
MDES	Minimum detectable effect size
NASFAM	National Association of Smallholder Farmers in Malawi
NN	Nearest-neighbour
ODK	Open Data Kit
OLS	Ordinary least squares
PICSA	Participatory Integrated Climate Services for Agriculture
PSM	Propensity score matching
Std. MDES	Standardized minimum detectable effect size
ToC	Theory of change
ToT	Training of Trainers
UNDP	United Nations Development Programme
UoR	University of Reading
WFP	World Food Programme
WHO	World Health Organization

EXECUTIVE SUMMARY

The timely provision of seasonal and short-term weather and climate forecasts is crucial for designing better adaptation strategies in agriculture and disaster risk management. With support from the United Nations Development Programme (UNDP), the Government of Malawi secured funding from the Green Climate Fund (GCF) to launch the project "Scaling Up the Use of Modernized Climate Information and Early Warning Systems (M-CLIMES)". The objective of the project is to reduce vulnerability to climate change impacts on lives and livelihoods, particularly of women, from extreme weather events and climate change.

The project supported the installation of 37 hydrological water level recording stations and installed 34 automatic weather stations. These stations extend existing coverage servicing both hydrological forecasting and localized weather data, to co-develop tailored weather- and climate-based agricultural advisories for dissemination through mobile, print and radio channels. The overall project cost is USD 16.3 million. The project is co-financed by the GCF (USD 12.3 million), UNDP (USD 1.8 million), and the Government of Malawi (USD 2.2 million) to support government efforts to respond to the challenge of climate change. The project is being implemented by the Department of Disaster Management Affairs in 21 of the country's 28 districts, over the period June 2017 to July 2023, and has been supported by other governmental agencies in Malawi.

One of the pillars of the M-CLIMES project is Participatory Integrated Climate Services for Agriculture (PICSA). Designed by the University of Reading and implemented in many countries, the PICSA component makes use of historical climate records, participatory decision-making tools and forecasts to help farmers identify and better plan agricultural activities that are suited to local climates and farmers' livelihoods. In Malawi, the PICSA approach involved the Department of Agricultural Extension Services in partnership with the National Smallholder Farmers Association of Malawi, who conducted trainings with groups of lead farmers ahead of the agricultural season to analyse historical climate information and use participatory tools to develop and choose crop, livestock and livelihood options. Over the period between 2018 and 2020, PICSA was rolled out in 14 districts in Malawi.

This report provides the first causal findings of the impact of PICSA on the farmers' adaptation decisions and food security. It is also aimed at highlighting challenges and obstacles encountered during implementation in order to enhance learning for the future implementations and scale-up of the programme. In this report, we aim to answer seven evaluation questions:

1. Did PICSA lead farmers attend the trainings?
2. Did they receive access to seasonal forecasts and short-term weather forecasts for rainfall?
3. Did they receive agricultural recommendations via SMS?

Compared to lead farmers who were not exposed to PICSA:

4. Were PICSA lead farmers more likely to make adaptations to their crop and livestock activities?
5. Did they increase agricultural yields (e.g. maize)?
6. Did they improve their wellbeing by reducing their work on the farms that belong to other farmers (a practice known as *ganyu*)?
7. Did they improve their level of food security?

To answer these questions, we rely on baseline and endline household surveys, which were collected before the start of the programme and two years after the first implementation, respectively. To

estimate causal impacts, we employ propensity score matching, in which we match the lead farmers who participated in the PICSA trainings in 2018 with farmers in districts where PICSA trainings were to be rolled out in 2020 (after the endline data collection). We base our analysis on a sample of 397 lead farmers surveyed in a total of eight districts in October 2020. We also triangulate our quantitative findings with the results from endline qualitative interviews with farmers, implementing partners and other programme stakeholders.

We estimate the causal effects of PICSA on several outcomes for lead farmers using propensity score matching. In the estimations, we apply different algorithms to ensure our results are not driven by the choice of method. We focus on the treatment on the treated impact estimates as we did not have access to all the information on the take-up and selection process of PICSA participants.

Our results suggest that PICSA had a statistically significant and positive impact on building the adaptation capacity of lead farmers who are facing the risks of climate change and climate variability. We find significant treatment effects on both intermediate and long-term outcomes, with magnitudes that are relatively similar across algorithms. With respect to intermediate outcomes, we find that PICSA lead farmers are much more likely to use seasonal forecasts to plan farm decisions (4 to 6 percentage points, control group mean: 1.9 per cent) and to make crop variety decisions (13 to 17 percentage points, control group mean:18.5 per cent). Similarly, the likelihood that PICSA lead farmers will make changes in crop activities is double that of non-PICSA farmers (29.5 to 36.4 percentage points, control group mean: 32.9 per cent). We do not find statistically significant effects on the number of crops grown or on the likelihood to make changes to livestock activities (at least, not systematically).

For long-term outcomes, we find that, as a result of PICSA, lead farmers in the treatment group register more than 434 to 505 kg/ha in annual maize yields than their peers in the control group. This represents a 60 per cent increase in yields compared to the control group. This finding largely diverges from the literature evidence on the effect of smallholder farming interventions. Systematic review evidence on the effects of farmer field schools finds an average impact of 13 per cent on yields (Waddington and others, 2014). When we compare this increase in maize yields to the trend in smallholder maize yields from 2002 to 2015 in Malawi, we note that the PICSA impact represents a broadly similar increase to that achieved over 13 years (see Prowse and Hillbom, 2018).

Finally, we observe that PICSA lead farmers are 9 to 16 percentage points less likely to work on other farms as a secondary source of income (control group mean: 29.2 per cent). We do not find significant impacts on food security as measured by food expenditures or the subjective measure of worrying about food shortage during the past 30 days.

Overall, the very large effect sizes registered for most outcomes urge us to be cautious in the interpretation of findings. In particular, we acknowledge that our evaluation suffered from a range of challenges and limitations, which include data quality and inconsistencies across two waves of data, including measurement errors in self-reported crop yields, missing information and other limitations. Despite this, we provide the first causal evidence from a GCF project that contributes to the literature on the effectiveness of adaptation programmes.

Overall, the positive evidence we report on the use of seasonal forecasts, changes to crop activities, yields and income is in line with benefits reported by lead farmers who attended PICSA trainings within the M-CLIMES project during 2019 performance monitoring assessments (Clarkson, Van Hulst and Dorward, 2020), in other PICSA assessments in Malawi (Steinmüller and Cramer, 2017) and in other countries (Clarkson and others, 2019; Clarkson and others, 2017; Dayamba and others, 2018).

Considering the positive impacts from the programme and the national agenda of Malawi to promote farmer-to-farmer knowledge exchange on adaptation practices, at the end of the report we provide policy suggestions for Malawi and similar contexts.

I. CONTEXT

1. 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 (Thornton and others, 2014; Jost and others, 2016). In the case of Malawi, 81 per cent of the population lives in rural areas, with the majority (89 per cent) of households engaged in agricultural activities (Malawi, National Statistical Office, 2017). Furthermore, agriculture is almost exclusively rain-fed: estimated irrigated land varies from 0.2 to 4 per cent (World Bank, 2018). The country is also particularly prone to natural hazards, and in the last few years it has experienced some of the most severe declared disaster events that have occurred since the establishment of the national disaster database in 1946 (World Bank, 2019). Due to El Niño, the 2015–16 rainy season 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 per cent of the population) would be unable to meet their food requirements (World Bank, United Nations and European Union, 2016).
2. The following agricultural cycle in 2017–2018 was also subject to erratic rains and was plagued by infestations of fall armyworms, causing an estimated crop loss of 20 per cent (World Bank, 2018). Most recently, in March 2019, Tropical Cyclone Idai impacted 15 of the 28 districts in Malawi, with floods and strong winds causing the loss of 60 lives and the displacement of more than 19,000 households (Malawi, 2019; Reuters, 2019).
3. Previous research on Malawi has shown that the impact of climate change on farmer households may depend on a variety of factors. For instance, Asfaw and Maggio (2018) show that households managed by women appear less vulnerable to temperature shocks in districts with a matrilineal land management system because their property rights are more secure. Meanwhile, rainfall shocks do not have any consistent impact (Asfaw and Maggio, 2018). Another factor that affects how households in Malawi respond to climate change is their wealth and the institutions that surround them (Asfaw and others, 2016). In particular, wealthier households seem more prone to use fertilizer and improved seeds to cope with greater climate variability. On the other hand, households that had more access to services and rural institutions increased their diversification and reduced their vulnerability to poverty (Asfaw and others, 2016). Furthermore, households' return to the adoption of sustainable agricultural practices varies by agroecological zone where the households reside. For instance, Maggio and Asfaw (2020) show that the adoption of hybrid seeds is positively correlated with aggregated yields only in the tropic-warm/subhumid and tropic-cool/semi-arid zones of Malawi.[1] These findings suggest that interventions should consider regionally specific characteristics.
4. Another factor limiting response capacity to climate change is the available information and uncertainty in terms of weather and climate risks, which may deter farmers from adopting new practices. Systematic reviews on smallholder farming training interventions find some positive evidence of the effectiveness of such interventions (Waddington and others, 2014; Stewart and others, 2015). Although there is inconclusive evidence on the adoption of beneficial practices (Waddington and others, 2014), there is some indication of positive results for farmers' knowledge and food security (Stewart and others, 2015). Regarding yields, Waddington and others (2014) indicate that in the studies they reviewed the impacts of farmer field schools may be in the region of

[1] Malawi can be divided into four broad agroecological zones: tropical warm/semi-arid, tropical warm/subhumid, tropical cool/semi-arid and tropical cool/subhumid.

a 13 per cent increase relative to comparison groups (farmers not enrolled in farmer field schools), although there is a large variation across target populations and contexts. However, most of these studies are not backed by rigorous theory-based evaluations (Waddington and others, 2014; Stewart and others, 2015).[2]

5. Large benefits are expected from the delivery of timely and tailored seasonal forecast information to farmers who can adapt their farming decisions accordingly (Hansen and others, 2011). However, research in this field is almost non-existent. Patt, Suarez and Gwata (2005) provide evidence suggesting benefits of seasonal forecasts to farmers. Their study piloted participatory workshops for farmers to promote the understanding and use of seasonal forecasts in four villages in Zimbabwe and found that the use of forecasts was associated with an average one year increase in seasonal harvests of 9.4 per cent.
6. In 2017, the United Nations Development Programme (UNDP), in partnership with the Government of Malawi through the Department of Disaster Management Affairs (DoDMA) and with funding from the Green Climate Fund (GCF), launched the project "Saving Lives and Protecting Agriculture-Based Livelihoods in Malawi: Scaling Up the Use of Modernized Climate Information and Early Warning Systems (M-CLIMES)". Besides strengthening the hydro-meteorological network capacity 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 via SMS.
7. A component of the M-CLIMES project is Participatory Integrated Climate Services for Agriculture (PICSA), designed by the University of Reading (UoR). This intervention is based on 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 20 different countries. However, to the best of our knowledge, it has not been assessed by rigorous impact evaluation techniques yet.
8. A beneficiary assessment of PICSA in one district (not covered by our evaluation) in Malawi and three districts in Tanzania (Steinmüller and Cramer, 2017) reported that nearly all of the farmers that 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 information 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. Evidence from performance monitoring of PICSA implementations in northern Ghana (Clarkson and others, 2019) indicates that 97 per cent of PICSA-trained farmers had made changes to their practices (mean of three per farmer) regarding crop, livelihood and/or livestock activities. As a result of the PICSA training, the majority (above 85 per cent) of farmers stated that PICSA benefited them in a number of ways, including higher household income and household food security. Qualitative information also indicated substantial improvements in farmers' yields. Similarly, encouraging findings were found in other contexts where PICSA has been implemented (Rwanda: Clarkson and others, 2017; Mali and Senegal: Dayamba and others, 2018).
9. This suggests that PICSA may be effective in terms of improved access and use of weather and climate information and that it may have some positive repercussions on the livelihoods of the participants.

[2] In addition, the rapid spread of cell phone ownership across developing countries has opened the possibility of delivering information directly to farmers. In Uganda, a programme based on agricultural information transmission via cell phones increased both the production of high-value crops and the bargaining power of the farmers at the time of selling their crops (Campenhout, 2017).

10. The present report contains the impact evaluation (IE) results of the PICSA intervention in Malawi. Section 0 describes the M-CLIMES project, PICSA, the implementation progress and the theory of change (ToC). Section I of the report builds on the ToC and programme implementation to define the set of evaluation questions and measurable outcome indicators for the IE. Section 0 describes the methodology used for the estimation of the causal effects of PICSA on the outcomes of beneficiary lead farmers, outlines the sampling strategy for the baseline and endline data collections, and discusses quality assurance and validation of data, ethics, and the software that was used for the data analysis. In the final three sections, we present the results and provide concluding remarks and policy recommendations.

II. PROJECT (INTERVENTION) DESCRIPTION

A. THE M-CLIMES PROJECT

11. The M-CLIMES project aims to increase the resilience of rural livelihoods to climate variability in Malawi. This is to be achieved through scaling up the use of modernized early warning systems (EWS) and climate information in the country. More specifically, the project plans to install new automated weather stations, build capacity, and deliver more accurate and better-customized climate information to vulnerable food-insecure, flood-prone and fishing communities in 21 districts out of a total of 28 in the country.

12. The M-CLIMES project aligns 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 Programme of Action (Malawi, 2017; Malawi, Ministry of Mines, Natural Resources and Environment, 2006). The project is being implemented by DoDMA in collaboration with a multiplicity of departments and institutions.[3] The project has three goals:

    1) The expansion of networks that generate climate-related data to save lives and safeguard livelihoods from extreme climate events.
    2) The development and dissemination of products and platforms for climate-related information/services for vulnerable communities.
    3) The strengthening of communities' capacities for the use of EWS/climate information in preparedness for response to climate-related disasters.

13. The impact evaluation team, which included the representatives of the Learning-Oriented Real-Time Impact Assessment (LORTA) programme, composed of staff from the GCF Independent Evaluation Unit (IEU) and the Center for Evaluation and Development (C4ED) (referred to as the LORTA team from this point on) and the staff from UNDP Headquarters visited the UNDP project team and their stakeholders in Malawi in September 2018. The task of the impact evaluation team was to engage closely with key stakeholders of the project – namely, the nationally designated authority, the accredited entity, implementing agencies, project staff and potential end beneficiaries – to ensure their interest, understanding and ownership of the planned theory-based IE.

14. During several workshop sessions, the ToC for each component under each goal of the M-CLIMES project and the related implementation plans were reviewed. For the IE, smallholder households were identified as the population of interest. The most suitable project component to evaluate was the PICSA intervention, representing goal 2 (above). This conclusion was reached based on restrictions in terms of budget and timeline. In addition, PICSA was the only activity that had been clearly defined and for which a roll out plan had been determined.

15. The following subsections detail the goals and modalities of PICSA and its implementation progress to date.

B. THE PICSA INTERVENTION

16. PICSA is a training-based intervention intended to empower farmers in making informed agricultural and livelihood decisions based on accurate, location-specific climate and weather information and the use of tools for participatory discussions. Training is delivered through a ToT

[3] These include the Department of Climate Change and Meteorological Services (DCCMS), Department of Water Resources, Department of Agricultural Extension Services (DAES), Department of Fisheries, and the National Smallholder Farmers Association of Malawi (NASFAM).

approach in which extension officers are first trained and are then responsible for leading training sessions of farmer groups.

17. The training activities are divided into 12 specific steps, which ideally start at least 8–12 weeks from before the beginning of the rainy season. These training activities guide 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.[4] Table II-1 describes each of the 12 steps and their related timelines, as suggested by the PICSA manual developed by the UoR (Dorward and others, 2015).

Table II-1. 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 and others (2015)

18. This structure defines the key PICSA activities, but the assigned facilitators can adjust the extent of the training and the overall logistics and planning of them to suit the local context. Overall, PICSA uses a farming systems approach to understanding and supporting the decision making of smallholders. Importantly, 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.

19. In Malawi, the PICSA intervention targets 14 districts that were identified as medium or highly food-insecure in the feasibility assessment for the M-CLIMES project (Government of Malawi, 2015). Due to capacity constraints, the timeline of the PICSA implementation was set to be phased in between 2018 and 2020 across groups of districts. By the time of the LORTA team's visit, UNDP, the Department of Agricultural Extension Services (DAES) and the National Smallholder Farmers Association of Malawi (NASFAM) had already selected the first group of districts, as well as the beneficiary farmers, and scheduled the launch of PICSA in those areas. 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 unit under the EPA level) were selected into treatment, depending on the actual

[4] Malawi has a single rainy season lasting from October/November to May.

presence of agricultural extension development officers (AEDOs) in each section and the specific AEDO's motivation and expected ability regarding the objective of PICSA.

20. The districts covered and the timeline of PICSA are presented in Table II-2. The district coverage was divided between DAES and NASFAM, but the overall implementation modalities were set to be uniform across the two entities. Importantly, PICSA is not only implemented by UNDP within the M-CLIMES project. The World Food Programme (WFP) has already been piloting PICSA in priority highly food-insecure districts as part of the Global Framework for Climate Services programme since 2015. UNDP and WFP coordinated the assignment of their respective areas of coverage for PICSA. Within those districts where both UNDP and WFP operate (Chikwawa and Zomba), the respective coverage was defined at the EPA level. The areas under WFP implementation are excluded from this IE study.

21. For the IE, the districts where PICSA was rolled out in 2018 – Dedza, Chikwawa, Ntcheu and Rumphi – were identified as the treatment group for the IE. The comparison group was defined as comprising the districts of Dowa, Lilongwe, Mzimba and Phalombe. Endline data collection was completed in the control districts before implementation.

Table II-2. PICSA roll-out

No.	Treatment status	District	Food-insecurity risk	Year of project implementation		
				2018	2019	2020
1	**Treatment**	**Chikwawa**	**High**	x		
2	**Treatment**	**Dedza**	**Medium**	x		
3		Chiradzulu	Medium		x	
4	Control	Dowa	Medium			x
5		Karonga	Medium		x	
6	Control	Lilongwe	Medium			x
7	Control	Mzimba	Medium			x
8		Nkhatabay	Medium		x	
9	**Treatment**	**Ntcheu**	**Medium**	x		
10		Ntchisi	Medium		x	
11	Control	Phalombe	High			x
12	**Treatment**	**Rumphi**	**Medium**	x		
13		Salima	Medium		x	
14		Zomba	High		x	

Source: LORTA and project teams
Notes: Food-insecurity risk information was retrieved from the feasibility assessment for the M-CLIMES project (Malawi, 2015). The remainder of the information is reported as discussed in the LORTA mission in September 2018 (Source: Own representation based on information provided by UNDP).

22. PICSA farmer groups were established based on the already existing farmer groups within DAES and NASFAM, following the "lead farmer" (LF) extension model employed by the Ministry of Agriculture and Food Security in Malawi. LFs are farmers selected by AEDOs as collaborators responsible for training other farmers – referred to as contact farmers (CFs) – in their villages on the technologies and topics promoted by the AEDOs. The implementation of the intervention was set to

follow the typical ToT approach as designed by the UoR. Firstly, UoR experts would train AEDOs, who would then be responsible for training LFs, who in turn would pass the information on to their CFs. In addition, refresher trainings to farmers were planned to be administered one year later in preparation for the next agricultural cycle.

C. Implementation progress

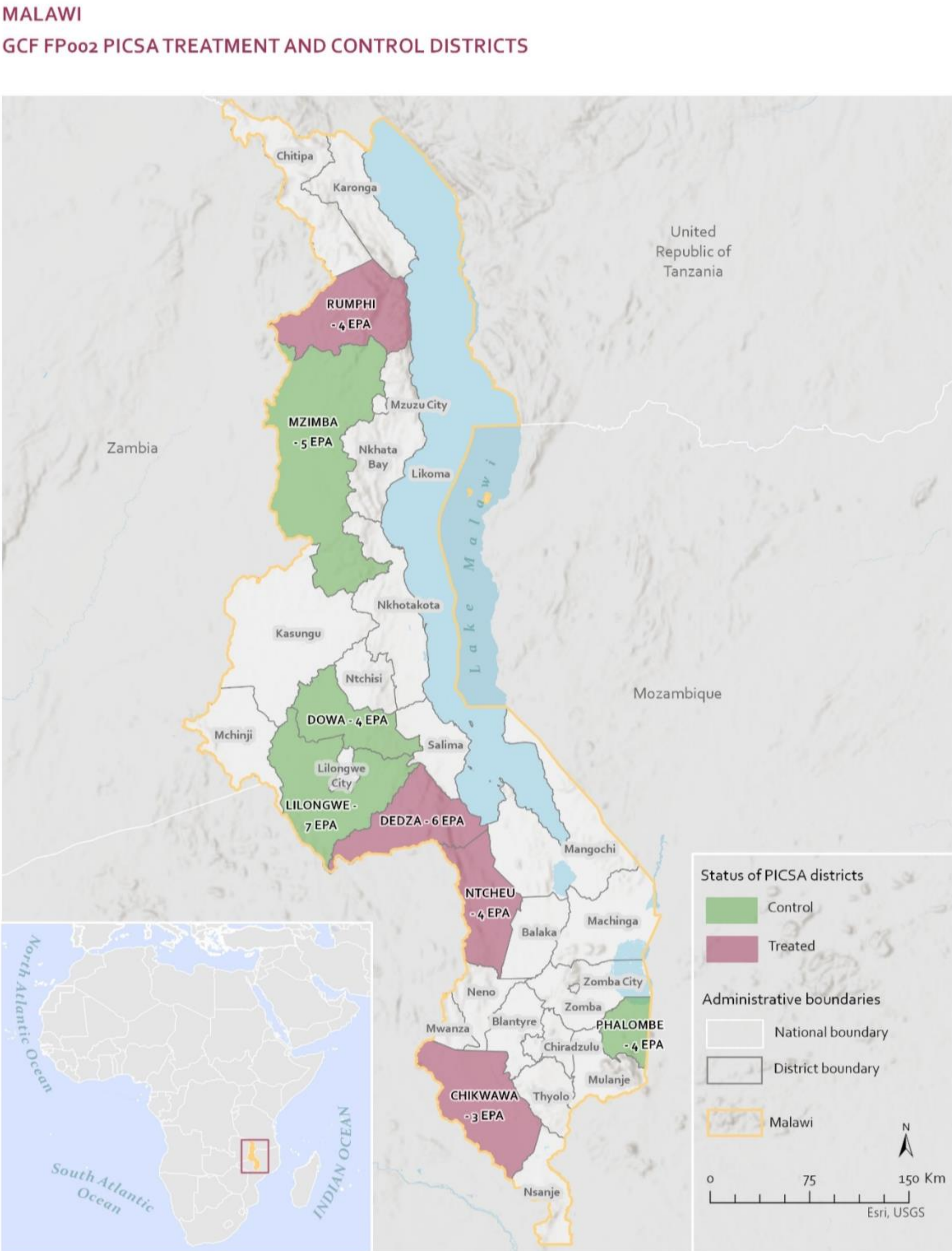
23. In August 2018, PICSA experts from the UoR trained 92 AEDOs and 30 government and UNDP stakeholders. The training sessions of LFs by AEDOs took place in October 2018 – a delay compared to the timeline suggested in the PICSA manual (8 to 10 weeks before the start of the rainy season) and with all topics condensed into one training event. The 92 AEDOs previously trained by the UoR imparted a four-day training to an average of two groups of 25 to 40 LFs within their agricultural section of competence in the four treatment districts: Chikwawa, Dedza, Ntcheu and Rumphi (called PICSA districts, henceforth). While no systematic record of training attendance at PICSA was carried out, the UNDP project team indicated that the targeted number of trained LFs was reached. A technical report on the evaluation of PICSA shared by the UoR – based on data from a random sample of trained LFs interviewed in June 2019 – reports that most attendees were trained on all the recommended PICSA steps (Clarkson, Van Hulst and Dorward, 2020).
24. The trainings of CFs did not take place according to plan. Due to delays in the delivery of trainings for the 2018 agricultural cycle in the PICSA districts, and due to capacity constraints, UNDP and the implementing partners shifted the trainings of CFs to 2019, together with the LF refresher trainings. However, the trainings for CFs were later discarded from the implementation due to capacity constraints. As a result, no trainings for CFs were conducted. Instead, during the PICSA training sessions, LFs were recommended to then share their learning with their respective CFs. The UoR's technical report indicates that – on average – interviewed trained LFs reported to have shared PICSA tools and information with 17 farmers outside their household (Clarkson, Van Hulst and Dorward, 2020).
25. In September 2019 – one year after the PICSA roll out – AEDOs and LFs received refresher training sessions. Firstly, one-day refresher training was conducted by the UoR to AEDOs. In turn, AEDOs oversaw the delivery of two-day refresher training sessions for their respective groups of LFs that they had originally trained in October 2018. These refresher training sessions consisted of summary revisions of specific PICSA topics based on feedback collected from PICSA LFs by the UoR researchers during the data collection for their evaluation in June 2019. Daily attendance at PICSA refresher trainings was recorded and the resulting attendance lists were collected and compiled by the UNDP project team. In parallel, in September 2019, PICSA was rolled out in six new districts: Chiradzulu, Karonga, Nkhatabay, Ntchisi, Salima and Zomba. Much like the implementation in the 2018 PICSA districts, each AEDO was responsible for training one new group of 25–40 LFs within their respective agricultural section. LFs were responsible for passing on their learning to their CFs. These districts are not covered by the IE study.
26. In October 2020, the 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) (see Figure II-1). The delivery of seasonal forecasts and short-term weather forecasts or early warnings is not included within the PICSA programme. Seasonal forecasts for rainfall are released at the district level once a year before the rainy season, which usually starts in October/November. They are accessible by the general farmer via TV, radio and extension officers. Short-term weather forecasts generally entail rainfall and temperature information every day, or every 5 or 10 days, and are broadcast via television and radio.

27. A further project component that was rolled out jointly by NASFAM and DAES overlaps with PICSA: the delivery of district level 10-day weather forecasts and agricultural recommendations to LFs via SMS.[5] In June 2018, DAES and NASFAM carried out a "profiling" exercise of AEDOs and LFs across the four treatment districts selected for PICSA for the delivery of agricultural advisories based on climate or weather information. DAES and NASFAM field reports indicate that data were collected from a total of 308 AEDOs and 4,718 LFs. Questionnaires were administered to LFs and AEDOs to gather their interest in receiving climate/weather-based advisories on crop and livestock subjects of interest as well as information on their specific activities. Based on this information and the agroecological and climate characteristics of their locations, LFs and AEDOs were selected to receive tailored messages.

28. According to the UNDP project team, the profiled LFs were highly likely to be selected into the PICSA component. The delivery of weather/climate and agricultural information services via SMS to farmers in our sample through NASFAM, DAES or other organizations was investigated in the endline survey. Results show that the proportion of PICSA LFs that reportedly received weather forecasts and advisory agricultural advisory via SMS from any source is rather low (14.4 per cent, i.e. 35 LFs, in treatment; and 5 per cent, i.e. 12 LFs, in control districts). Discussions with NASFAM staff at the time of the endline evaluation revealed that the implementing partner was still working on profiling LF names and their phone numbers in some districts. As a result, the majority of LFs' phones were not yet connected to the SMS service. Because of this, LFs still mainly accessed weather forecasts through their extension workers who were receiving the SMS from the Department of Climate Change Management Services (DCCMS) via their phones.

[5] Among its project targets, the M-CLIMES project aims to enhance the accuracy of the meteorological information produced. This will be possible in the medium term as historical meteorologic data will be collected from newly installed stations across Malawi as part of the project. For the time being, the accuracy of weather forecasts delivered via SMS has not been improved with respect to the baseline levels described in the feasibility assessment for the M-CLIMES project (Malawi, 2015). Information services via SMS were in place before M-CLIMES; however, those delivered to farmers associated with NASFAM only included weather forecasts as issued by DCCMS. Furthermore, the service was in place in fewer districts.

Figure II-1. 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.

Table II-3. 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 programme implementation	
Winter season		
June 2018	Profiling data collection to gather interest for tailored messages	308 AEDOs and 4,718 LFs (profiled LFs were likely to be selected into PICSA)
August 2018	92 AEDOs trained by UoR	
Since October 2018	308 AEDOs and 4,718 LFs started receiving climate/weather-based advisories on crop and livestock	
October 2018	Baseline data collected	Total sample size: 1,802
Harvesting ends and the rainy season starts		
October 2018	Two groups of 25–40 LFs 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 LFs	On average, LFs shared information with 17 CFs
September 2019	AEDOs and LFs received refresher training sessions, by UoR (1 day) and AEDOs (2 days) respectively	
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

D. Theory of change

29. The ToC is a logical mapping illustration describing the required steps to achieve the long-term goals of an intervention and the necessary assumptions linking one step to the next. Figure II-2 illustrates the ToC for the PICSA intervention.

30. The logical steps are as follows:

1) **Inputs:** While the budget is provided by UNDP Malawi through GCF funding, the input in terms of staff comes from the implementing partners – namely, DAES and NASFAM. The content of the PICSA programme is designed by researchers from the UoR, who also carry out the training of AEDOs and adapt the content of the PICSA programme to the Malawian context.

2) **Activities:** The actions at the core of the PICSA programme are trainings on interpreting seasonal forecast information, using historical data to make seasonal forecasts, assigning probabilities to different weather events, jointly discussing what climate-resilient practices are

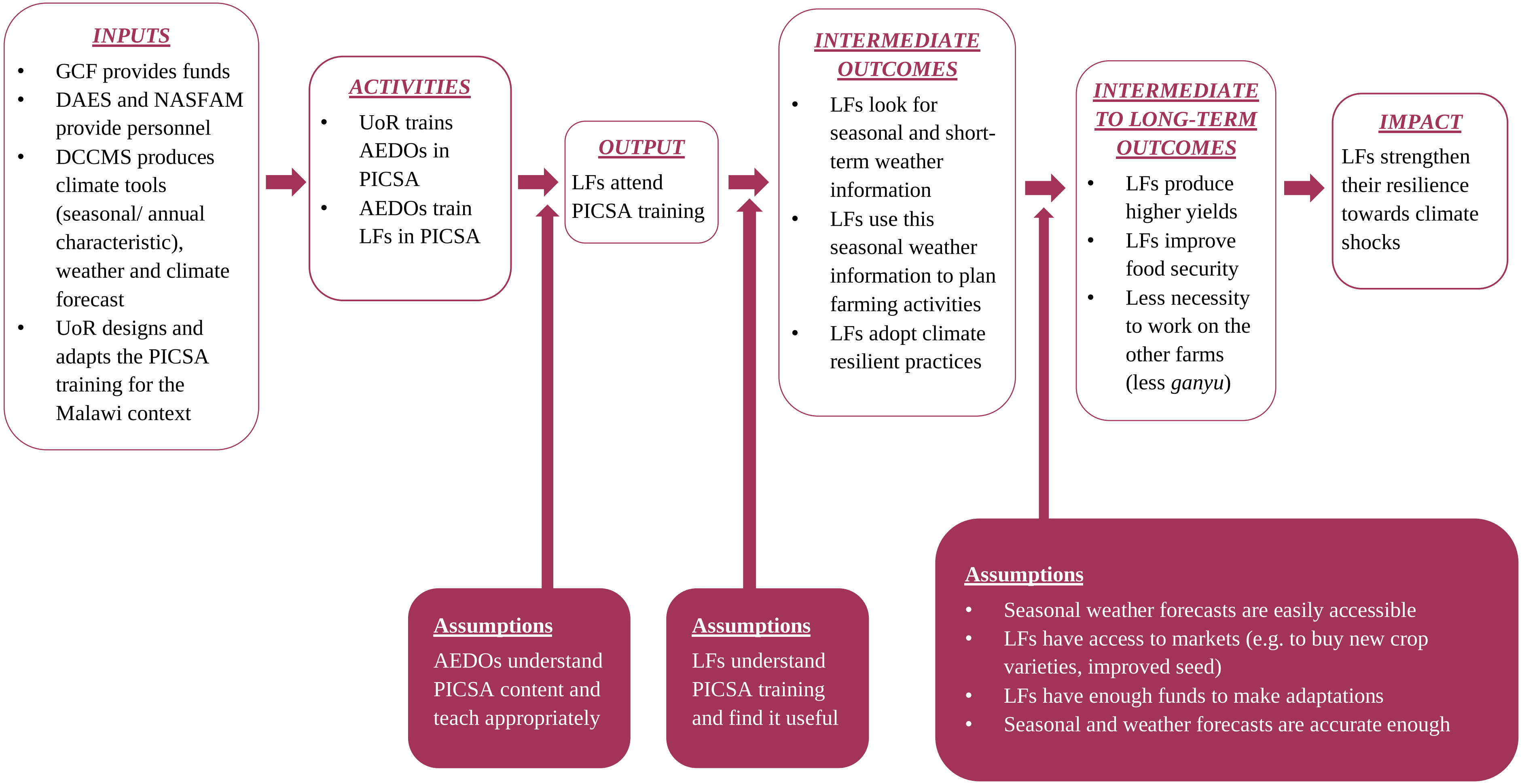
available to them, budgeting and planning resources and activities, and understanding short-term weather forecasts and warnings. First, the UoR trains AEDOs, who subsequently train the LFs.

3) **Outputs:** Successful activities result in LFs attending the training sessions.
4) **Short-term outcomes:** LFs look for seasonal/weather information, make use of acquired knowledge and information to plan for agricultural activities, and adopt climate-resilient practices.
5) **Intermediate to long-term outcomes:** Assuming positive changes in the intermediary outcomes, LFs are expected to achieve higher agricultural yields and improve their food security.
6) **Impact:** An impact of the PICSA intervention is the resilience of farmers' livelihoods to climate risks.

31. Importantly, a set of assumptions connects each step to the next, as shown in Figure II-2. Key assumptions are that LFs who attend the PICSA training sessions better understand seasonal and weather forecasts, the available adaptation options and how to apply them. Furthermore, the ToC hypothesizes that LFs can easily access seasonal and weather forecasts, perceive them as trustful and useful, have enough funds to adapt their farming decisions, and have access to markets to retrieve the necessary inputs. Finally, seasonal forecasts need to be accurate enough to generate benefits in terms of yields for the farmers who adjust their agricultural activities accordingly.
32. We do not expect that the CFs, who correspond to each LF, are significantly impacted by the programme. Firstly, they were not formally trained by their LFs. Secondly, we could not track the transmission of information from the LFs to their CFs. Finally, as we realized from the baseline and follow-up surveys, not all CFs who were planned were surveyed. Therefore, we have discrepancies between the two survey waves and incomplete clusters (for example, an LF with no CF, or CFs without an LF). The current ToC does not include possible impacts on the CFs.[6]

[6] Our view that CFs are not significantly impacted by the programme is also based on feedback from the LORTA seminar and discussions with the UoR, their views on the PICSA ToC, experience of implementation in Malawi and other countries, and the outcome indicators and impacts.

Figure II-2. The M-CLIMES–PICSA theory of change



Source: LORTA team based on information by UNDP.

III. EVALUATION QUESTIONS AND INDICATORS

33. The ToC as well as project implementation updates guided the formulation of the evaluation questions (EQs), which are tested in the endline analysis to inform whether the implementation of PICSA had an impact on the outcomes. After thorough discussions with the project team and the UoR researchers who designed and monitored the PICSA implementation, the final focus for the IE was restricted to LFs only. As described above in the project description section, the implementation of the ToT chain terminated at the level of the LFs. Although the LFs were recommended to share their learnings with their respective CFs, based on UoR's field monitoring observations, there is no expectation of a behavioural change for CF households.

34. Table III-1 shows that success is assessed via the EQs at four levels along with the ToC. The first set of EQs focuses on the delivery of outputs as planned by the programme: attendance at PICSA training sessions and access to weather information and agricultural recommendations via SMS. Second, short-term outcomes are access to seasonal and short-term weather warnings for rainfall.

35. The IE reports on average intermediate and long-term outcomes observed at endline for the treatment and the control group. The intermediate outcomes we consider whether households make adaptations to their crop activities and livestock activities. The long-term outcomes are the changes in crop and livestock activities, yields, secondary sources of income, and food security.[7]

Table III-1. Evaluation questions

Temporal ToC step	EQ	Description
Outputs	1	Did lead farmers attend the PICSA trainings?
	2	Did lead farmer households have access to weather information and agricultural recommendations via SMS?
Short-term outcomes	3	Did lead farmer households have access to seasonal and short-term weather warnings for rainfall?
Intermediate outcomes	4	Did lead farmer households make adaptations to their crop activities and livestock activities?
Long-term outcomes	5	Did lead farmer households increase yields?
	6	Did lead farmer households improve their well-being by reducing their work on other farms (*ganyu*)?
	7	Did lead farmer households improve their level of food security?

Source: Impact evaluation team

36. The EQs were translated into measurable outcome indicators, thereby setting the scope of the IE. For the causal analysis, we focus on analysing intermediate and long-term outcomes (EQs 4–7). Table III-2 presents the main indicators that we could retrieve from the endline survey. To answer EQ 4, we capture whether the LF household used seasonal forecasts to plan farm decisions and to make crop variety choices during the last rainy season (2019).[8] Furthermore, we measure whether the LF

[7] The initial plan (as per the ToC) was to additionally test the assumptions as well as the longer-term goals. However, based on project updates and limited capacity and data constraints, it was decided to focus on outputs, intermediary outcomes and long-term outcomes.
[8] Unfortunately, we do not have information on the usage of short-term forecasts by lead farmers in the data (the number of responses is very low).

made changes to crop activities and the number of crops grown during the last rainy season. Following Clarkson, Van Hulst and Dorward (2020) the following changes to crop activity were considered: changed management of land, changed type or number of inputs, changed planting dates, decreased the scale of a crop/variety, increased the scale of a crop/variety, grew a new or a different crop/variety, changed irrigation schedule, and made investments in irrigation.

37. While the variables for whether farmer households used seasonal forecasts to plan farm decisions and to make crop variety choices during the last rainy season are focused specifically on seasonal forecasting, the two outcomes of making changes to crop activity and the number of crops grown during the last rainy season are more general. Some of these four types of indicators may be overlapping, but we include them for robustness checks and to see whether we observe a more general impact on crop activity, rather than solely crop diversification, and whether seasonal forecasting played a role in the decision-making.

38. The final intermediate outcome is if an LF made any changes to their livestock activities. In line with Clarkson, Van Hulst and Dorward (2020) we measure the following changes to livestock activity: started a new livestock activity, increased the scale of a livestock activity, decreased the scale of livestock activity, changed the management of livestock activity, or tried a new breed of livestock.

Table III-2. Indicator descriptions and measurement

EQ	Indicator	Type	Measurement
Outputs			
1	Attended any PICSA training	Dummy	1 if LF attended any PICSA training (2018/2019), 0 otherwise. Measured for the treatment group only.
1	Attended 2018 PICSA training	Dummy	1 if LF attended the 2018 PICSA training, 0 otherwise. Measured for the treatment group only.
1	Attended 2019 PICSA refresher training	Dummy	1 if LF attended the 2019 PICSA training (2018/2019), 0 otherwise. Measured for the treatment group only.
2	Received agricultural recommendations via SMS during rainy season 2019	Dummy	1 if LF received any agricultural recommendations via SMS in 2019 rainy season, 0 otherwise. Measured for the treatment group only.
Short-term outcomes			
3	Accessed seasonal rainfall forecasts in the 2019 rainy season	Dummy	1 if the household accessed seasonal rainfall forecast predicting high or low rainfall for the 2019 rainy season
3	The primary source of seasonal rainfall forecasts for the 2019 rainy season	Dummies per category	For each dummy, 1 if the LF household indicated the respective source of seasonal rainfall forecast, 0 otherwise
3	Type of rainfall information included in seasonal forecasts for 2019 rainy season	Dummies per category	For each dummy, 1 if the LF household indicated the respective source of seasonal rainfall forecasts they accessed, 0 otherwise
3	Seasonal forecasts for 2019 rainy season included information for own district	Dummy	1 if the LF household recalled that 2019 seasonal rainfall forecasts they accessed included information for own district, 0 otherwise
3	Seasonal forecasts in the 2019 rainy season included maps	Dummy	1 if the LF household recalled that 2019 seasonal rainfall forecasts they accessed included maps, 0 otherwise

EQ	INDICATOR	TYPE	MEASUREMENT
3	Accessed seasonal rainfall forecast for 2019 rainy season in time for use	Dummy	1 if the LF household reported that they accessed the 2019 seasonal rainfall forecasts in time to use, 0 otherwise
3	Accessed short-term rainfall warnings in rainy season 2019	Dummy	1 if the LF household accessed short-term rainfall warnings during 2019 rainy season, 0 otherwise
Intermediate outcomes			
4	Used seasonal forecasts to plan farm decisions	Dummy	1 if an LF household reported using seasonal forecast to plan farm decisions in 2019 rainy season, 0 otherwise
4	Used seasonal forecasts to make crop variety choices	Dummy	1 if an LF household reported using seasonal forecast to make crop variety choices in 2019 rainy season, 0 otherwise
4	Made changes to crop activities	Dummy	1 if an LF household made changes to crop activities in the 2019 rainy season, 0 otherwise
4	Number of crops grown*	Continuous	Number of crops grown in 2019 rainy season
4	Made changes to livestock activities	Dummy	1 if an LF household made changes to livestock activities in the 2019 rainy season
Long-term outcomes			
5	Maize yield	Continuous	Yield (kg/ha) of maize in 2019 rainy season
6	*Ganyu* income source	Dummy	1 if an LF household earns income from casual labour, 0 otherwise
7	Worried about food shortage	Dummy	1 if an LF household worried about not having enough food during the past 30 days
7	Ln of food expenditures	Continuous	Natural logarithm of total household food expenditures during the last 30 days

39. Under EQ5, we focus on maize yields, as maize is the main food crop (measured as kilograms per hectare) grown in Malawi.[9] In EQ 6, we capture whether an LF household earns income from casual labour as a secondary source of income (known as *ganyu*). *Ganyu* is 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 a coping strategy for the poorest households in Malawi (Whiteside, 1999).

40. Finally, we answer EQ 7 with two food security indicators: (1) if an LF household worried about not having enough food during the past 30 days, and (2) their food expenditures[10] within the same reference period.

[9] Major food crops in rural Malawi are maize followed by soybeans and groundnuts. Maize is a universal and staple food crop grown in all districts of the country, whereas groundnuts and soybean are mostly grown in the central region of the country in such districts as Ntcheu, Dedza, Lilongwe and Dowa.

[10] We smooth this food-expenditures indicator by taking a natural logarithm of the monetary values plus 1.

IV. EVALUATION DESIGN AND STRATEGY

A. Methodology

41. This evaluation was designed to employ a mixed-methods approach – that is, combining quantitative and qualitative data. The quantitative analysis aims to assess compliance with the implementation and to estimate the causal effect of PICSA on LFs. The strategy to identify the causal effect of PICSA employs propensity score matching (PSM), which is a departure from what was originally proposed in the LORTA design report. The methodology originally proposed was difference-in-differences coupled with matching. However, this was later revised due to challenges and quality issues associated with the baseline data. In particular, the difference-in-differences technique was no longer considered suitable due to the lack of several indicators (e.g. access to seasonal forecasts, food security, and other matching and outcome variables) and due to pitfalls in the measurement of indicators at baseline (e.g. adaptation practices, yields).

42. Qualitative data were collected at baseline and endline in order to provide complementary and insightful evidence on how PICSA is implemented, the challenges, the gendered impacts of PICSA, and the sustainability of PICSA. The qualitative methodology is based on the narrative analysis of key informant interviews and focus group discussions. We do not present the findings from the qualitative component in this evaluation but describe the designed approach in Appendix 1.

43. In the following subsections, we elaborate in detail on the quantitative methodology for the IE, describing the evaluation design based on the PSM technique, the survey sampling strategy and the sample structure at baseline and endline, as well as the data-collection tools. We provide a summary description of the qualitative methodology in Appendix 1.

B. Design

44. This subsection presents the evaluation design for the IE. The focus will be on estimating the causal effects of PICSA on the outcomes of beneficiary farmer households. In the following subsections, we describe the identification strategy applied for the identification of causal effects based on the PSM methodology as well as the empirical estimation strategy.

1. Identification of causal effects

45. The PSM technique seeks to estimate the effect of the PICSA intervention as the observed differences in outcomes between beneficiaries and non-beneficiary households sometime after the roll out of the programme, while adjusting for other observed factors that may account for further differences between them that are not attributable to the intervention under study. Based on the PSM technique, the effect of the programme on beneficiary households is identified via the following equation:

$$E\big(Y\big|D = 1, p(X)\big) - E(Y|D = 0, p(X)) \qquad (1)$$

where D is a binary indicator of treatment status and $p(X)$ is the propensity score – that is, the probability of selection into treatment estimated as a function of a chosen set X of observed variables. In other words, the effect is identified from the difference in outcome Y between the treatment group $(D = 1)$ and the control group $(D = 0)$ while adjusting for the propensity score.

46. We define the PICSA treatment as attendance in any PICSA training, from the first training rolled out in 2018 to later refresher training rolled out in 2019. We are interested in estimating the effect of

PICSA on the LFs that voluntarily participated in the training sessions – that is, the intended beneficiaries that were "actually" treated,[11] known as "compliers". In the IE terminology, the identified treatment effect is referred to as the "average treatment effect on the treated". Note that although the delivery of agricultural SMS services overlapped with PICSA, results show that the profiling of LFs is still in progress and only a minority of those in the treatment group have effectively been reached so far. We therefore attribute the estimated impact mainly to the PICSA intervention.

47. The PSM identification strategy relies on the observability of all factors potentially affecting the selection into the intervention and each of the outcomes of interest. Then, conditional on these factors, matching establishes comparability between treatment and control group, and any difference in outcomes detected between the two groups is solely attributed to PICSA.
48. In the next subsection, we elaborate on the observed variables (matching variables) chosen to estimate the propensity score and related limitations.
49. Another important condition for PSM is that enough common support in the propensity scores of the treatment and control groups exists. This means that each PICSA LF must have a counterpart with a similar propensity score in the control group.
50. We estimate the effects of PICSA on the intermediate and long-term outcomes of interest for LF households in line with the ToC. Due to the limited total sample size, we do not extend the analysis to explore heterogeneous treatment effects across LF households by estimating the propensity score conditional on, for example, the gender of the household head or income.[12]
51. As with income or poverty heterogeneity, we lack reliable baseline measurements of monetary income, expenditures and poverty indicators. We include proxies of household welfare based on dwelling characteristics and agricultural asset ownership in the set of matching variables. As with gender, stratifying an already limited sample into smaller subsamples based on these variables would have led to insufficient statistical power for the identification of impact.

2. Empirical strategy

52. The PSM estimation procedure comprises two main steps. In the first step, the probability that a farmer is selected into the PICSA intervention – known as the propensity score – is estimated with the use of a binary model such as a logit model. In the second step, farmer households in the treatment group are matched based on a chosen algorithm to farmers in the control group with similar propensity score values. The matching can be performed provided that enough common support in the propensity scores of the two groups exists. This means that each PICSA LF must have a counterpart with a similar propensity score in the control group.
53. We estimate the impacts of PICSA on the intermediate and long-term outcomes of interest using several matching algorithms using the propensity score: (1) 1-1 matching, (2) nearest-neighbour (NN) matching with two or six nearest neighbours, (3) radius matching with 0.2 caliper, and (4) kernel matching using the Epanechnikov kernel function, with 0.06 and 0.1 bandwidth. We use different matching algorithms to test the robustness of the results.

[11] Note, therefore, that IE results are not representative of LFs that were selected by PICSA but chose not to participate.
[12] In the sample for the PSM analysis, there are 92 female-headed households. The comparison drawn from such a small sample size distribution would not provide us with a credible conclusion on the gender differences. Qualitative interviews with implementing partners conducted by the endline survey firm revealed that most LFs participating in the PICSA trainings were female. Yet heterogenous analysis by the gender of the LF is also not possible, due to missing information in the data set for a large share of the sample.

54. When applying the 1-1 matching estimator, one LF observation from the treatment group is matched with a neighbouring control group observation, defined as the closest control observation based on the propensity score value. To improve the precision of the estimates, we used 1-1 matching with replacement, which enabled us to match one control household to multiple treatment households. We also allowed for more control LFs to be matched as nearest neighbours (2 and 6) to treatment LFs, with replacement.
55. The radius matching with caliper performs matches based on the number of similar observations in a local neighbourhood (the "caliper"). Matching pairs of treated and control LFs are formed whose propensity scores differ by at most a pre-specified amount (the caliper width). We use the optimal caliper width of 0.2 as suggested by Austin (2011).
56. The kernel estimator matches one treatment household with a weighted average of all the pure control households within a given propensity score distance ("bandwidth") to the treatment household. The assignment of weights (the closer the propensity score of a pure control household to the treatment household, the higher the weight) is done through a specific function ("kernel" function). We use the Epanechnikov kernel function with a bandwidth of 0.6 (the default Stata option from Leuven and Sianesi (2003)) and 0.1. The use of multiple algorithms for matching enables assessing the robustness of results in terms of stability of estimated coefficients and the statistical significance for the treatment effects.
57. For 1-1 matching and NN matching, we use Abadie–Imbens standard errors (Abadie and Imbens, 2006, 2016). For the radius matching with a caliper, we use approximate standard errors on the treatment effects assuming independent observations, fixed weights, homoskedasticity of the outcome variable within the treated and the control groups, and that the variance of the outcome does not depend on the propensity score. For the kernel matching estimator, we bootstrap standard errors with 1,000 replications.

3. Matching variables

58. As described above, the choice of matching variables to estimate the propensity score is crucial as it determines the quality of the comparability between the treatment and control group. Ideally, all factors affecting the selection into the intervention and of the outcomes of interest are included in the propensity score model.
59. Unfortunately, we do not have exhaustive information on the selection process of LFs into PICSA. The existence of any unobserved factor correlated with the outcomes of interest and differentially affecting treatment and control LFs would inevitably bias to some extent the measurement of causal effects. Furthermore, as Smith and Todd (2005) note, there is little guidance available on how to select the set of matching variables used to construct the propensity score. Thus, we focused on finding a set of matching variables that were highly associated with the programme eligibility and the outcome variables. We ran various specifications before finalizing the set of the matching variables in order to strike a balance between having good common support and an exhaustive set of observed factors that may alter participation in the programme and the outcome variables.
60. Our starting point in the selection of matching variables was the substantial literature on participation in extension schemes and the finding that richer and networked smallholders in general benefit from better access to extension advice than poor smallholders in many developing countries (see Chambers, 1983; Christoplos, 2010; Haug, 1999; Mosse, 1993; Rivera, 2011; Swanson and Rajalahti, 2010). Our approach to judging the welfare level of rural households is based on assets

owned or the type of house a family lives in.[13] We include a range of household-level variables that represent different asset categories. These are ownership of basic assets such as land and livestock, as well as if the family has access to electricity, 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 (WHO)).[14] Pre-intervention demographic variables such as gender, age, education level of the household head and family size are also included. Household access to a cell phone is included because it could be an important factor for selection into the programme, as farmers were to receive seasonal and short-term forecasts by SMS (although, as we reported in section II.C, the percentage of LF households that received the SMS forecasting was rather low at the time of the endline survey). One factor that was mentioned as a key criterion for selection into PICSA at the time of the LORTA visit, was the intrinsic motivation and connectedness of farmers. While these characteristics cannot be observed in the data, we attempt to control for them by including the baseline number of CFs per LF and the number of yearly visits of LFs to CFs as proxy variables. While the ratio of CFs per LF could be an indication of connectedness and "power", the number of field visits could serve as a proxy for an LF's productivity and motivation.

61. Another proxy of connectedness that can be found in rural communities in Malawi is practising religion together. Unfortunately, we do not have this information at the baseline, but we do have a variable that indicates the contribution of the farmer household towards a church or a mosque. This serves as a proxy of not only being involved in religious activities together with others but also income status. As we do not have a reliable measure of the pre-intervention household income, this serves as a credible substitute.

62. Other LF-level characteristics (such as the technology they promote) are excluded from the model due to a large number of missing values in the data set.

63. We also include matching variables such as the households' proximity to basic infrastructure – namely, closest agricultural market.

64. Other important factors explaining underlining differences between treatment and control LFs depend on the exposure to climatic conditions and weather-related hazard events. Among these, droughts and floods represent a major challenge (Malawi, 2015).

65. We control for differential geo-climatic characteristics between areas where treatment and control LF households reside and the differential risk exposure to weather and climatic events using municipality-level data on pre-intervention temperature, rain patterns and elevation. Temperature and precipitation come from the CRU TS data set,[15] and we use information from the rainy seasons starting from October 2012 through to May 2018. We collected these data on the AidData.org portal and matched it with the latitude and longitude locations of our households and municipality boundaries in ArcGIS.

66. Figure A - 1 in Appendix 4 illustrates the elevation of various municipalities and the location of the LF households, Figure A - 2 illustrates the average temperature over the rainy seasons between October 2012 and May 2018, Figure A - 3 illustrates the average precipitation during the same rainy seasons, and Figure A - 4 illustrates the total precipitation.

67. One large scale hazard event that recently affected Malawi was Tropical Cyclone Idai, which hit the country in March 2019 and caused heavy rains and floods in 14 districts, including one control

[13] Examples of studies that illustrate this approach in combination with a range of statistical methods include Mahmud and Prowse (2012), and Sakketa and Prowse (2018).
[14] As defined by the Joint WHO & UNICEF Monitoring Programme (JMP), an improved drinking-water source is one that by the nature of 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.
[15] Link to the Aiddata portal *http://geo.aiddata.org/query/#!/* and the dataset *High-resolution gridded datasets (uea.ac.uk).*

district (Phalombe) and three treatment districts (Ntcheu, Dedza, Chikwawa) in the IE sample (Malawi, 2019). This affects the comparability of treatment and control districts. However, the matching on pre-intervention exposure to high precipitation should lessen this bias.[16,17]

68. With this rich set of control variables (Table IV-1), we could capture many of the determinants of participation, which may also serve as a proxy for some unobservable traits.

Table IV-1. Matching variables description and measurement

VARIABLE	TYPE	MEASUREMENT
Gender of household head	Dummy	1 if household head is male, 0 otherwise
Age of household head	Continuous	Age of household head in years
Household size	Continuous	Number of members in a household
Primary School	Dummy	1 if a household head completed primary school, 0 otherwise
Access to cell phone	Dummy	1 if a household has access to a cell phone, 0 otherwise
Access to electricity	Dummy	1 if a household has access to electricity, 0 otherwise
Iron sheet roofing	Dummy	1 if a household owns a house with iron sheet roof, 0 otherwise
Brick/concrete walls	Dummy	1 if a household owns a house with brick/concrete walls, 0 otherwise
Improved water source	Dummy	1 if a household uses improved water source (WHO classification), 0 otherwise
Owned land size	Continuous	Size of the largest single plot area (in ha)
Church/mosque contribution	Continuous	Ln of the church/mosque monthly contributions plus 1
Livestock income source	Dummy	1 if a household earns income from livestock, 0 otherwise
Number of CFs for each LF	Continuous	Number of CFs for each LF
Number of field visits	Continuous	Number of field visits by an LF to the CF
Village avg. distance to market (km)	Continuous	Average village distance to a market (km)
Municipality avg. precipitation (mm) during rainy seasons 2012–2018	Continuous	Municipality average monthly rainfall (mm) across all months in the rainy season (Oct–May) in 2012–2018
Municipality avg. temperature (°C) during rainy seasons 2012–2018	Continuous	Municipality average monthly temperature (°C) across all months in the rainy season (Oct–May) in 2012–2018
Municipality avg. elevation (m)	Continuous	Municipality average elevation (m)

[16] We do not condition on exposure to this event, which is ex-post the PICSA intervention, as it would bring more bias into the estimation (vulnerability to climate hazards is affected by the treatment).
[17] The project's feasibility assessment (p.18) classifies Malawian districts by the number of households affected by the floods over the past 10 years. We constructed a "flood risk" variable for each district in our sample. However, we do not use it in our final specification because it varies quite substantially from district to district, thereby substantially reducing the common support.

C. Sampling strategy and data collection

69. Two waves of data collection were carried out. The baseline survey took place in October 2018 and the endline survey two years later, in October 2020. In the following subsections, we describe the sampling strategy at baseline and at endline, as well as the attrition and the final sample used for analysis.

1. Baseline survey sample

70. The unit of analysis is the farmer household. Because of the clustered structure of the ToT approach used in the implementation of PICSA, a clustered sampling approach was applied. A cluster was defined at the level of the LF. The baseline sampling strategy for the household survey targeted two farmer groups: LFs and CFs. Each treatment arm would consist of 225 clusters comprising four farmers each: one LF and three respective CFs. The sample size was informed by power calculations (see Appendix 2 and Appendix 3).

71. The Centre for Development Management (from now on “the baseline survey firm”) was contracted for the baseline data collection and evaluation. The sampling frame in the treatment districts was the list of the PICSA LFs selected for the trainings based on lists that were compiled and shared by the UNDP project team. Then a random sample of three of their CFs was to be interviewed. The sampling strategy in the control districts was to replicate the PICSA selection procedure followed in the treatment districts.

72. The baseline survey was planned for a random sample of farmer households in each of the two groups of districts (treatment and control). Unfortunately, due to lack of available farmer lists and logistical constraints, a proportion of them was selected by referral sampling, especially in the control districts, where lists of farmer-beneficiaries were not available. While this is a limitation, it was mitigated using the PSM technique, which constructs the counterfactual based on a selective group of control farmer households that are the most comparable to the ones in the treatment group.

73. The actual baseline sample comprised a total of 1,802 households. However, several challenges were present in the data (see section 0D). The main issue related to the sample structure was the fact that the farmer status, and therefore cluster relationship (LF and respective CFs), was not observed for several farmer households.

74. Table A - 1 in Appendix 2 displays the sample structure for the CFs belonging to clusters for which both LFs and CFs were observed in the baseline data set (we refer to these clusters as “complete”). Another divergence from the baseline strategy was the variation in the number of CFs interviewed per cluster.

75. The missing information on the farmer household status was addressed to the extent possible by LORTA team in collaboration with UNDP, DAES and NASFAM. The baseline data set was then shared with the endline survey firm (see below) as a sampling frame for the endline data collection; they then verified the above information in the field.

2. Endline survey sample and attrition

76. The endline sampling strategy was to track and re-interview all farmer households interviewed at baseline. The Centre for Independent Evaluation (CIE, “the endline survey firm” from now on) was contracted for the endline data collection and evaluation. They successfully re-interviewed 1,642 households. The attrition rate was relatively low (8.8 per cent) and accounted for households that could not be traced due to either death, relocation or sickness. As can be seen in Table IV-2, the

attrition rate was slightly more pronounced in the treatment group than in the control group, with a difference of 2 percentage points between the two.

Table IV-2. Completed interviews by treatment status

Treatment status	Completed interviews			Target (N. obs.)	Attrition rate (%)
	LFs	CFs	Total		
Treatment	251	559	810	896	10
Control	233	601	834	903	8
Total	484	1,160	1,644	1,799	9

Source: Impact evaluation team
Note: Three baseline household interviews were duplicated (same farmer respondent but recorded at baseline under different names) in the listing of farmer households to be tracked at endline, hence the target sample size was 1,799 as opposed to 1,802. Attrition rates disaggregated by source were not recorded during the endline data collection.

77. If differential attrition was affected by the treatment, it would affect the external validity of the IE – that is, the endline sample may not be representative of the targeted farmer households. The use of the PSM technique adjusts for the observed imbalance in characteristics between treatment and control groups before estimating the effect of the intervention. Therefore, holding the observability identification assumption, differential attrition is not considered a threat to internal validity.
78. The evaluation focus was later narrowed down to the impact of PICSA for LFs only, regardless of whether they belonged to complete or incomplete clusters. After the end of the contract with the endline survey firm, the analysis has been taken over by the LORTA team and the sample was further adjusted for analysis (see section 0D).
79. The final sample used for the analysis amounts to 494 LFs. As per the estimation strategy outlined earlier, the sample used in the PSM analysis comprises LFs that attended at least one PICSA training in the treatment districts (163) and all LFs (234) in the control districts.

3. Data-collection tools

80. The quantitative evaluation combines primary and secondary data sources. The baseline survey captured a wealth of information, including general demographic, social and economic characteristics of a farmer's household; characteristics of the farmer; the farmer's climate awareness and experience of multiple natural hazards, along with access, understanding, and use of weather and climate warnings; agricultural information including crop yields and land size; and the farmer's adaptation practices. However, the data lacked information on key indicators for the evaluation, such as access to seasonal forecasts, and presented measurement issues for some of the collected indicators (e.g. adaptation practices, yields). For this reason, this data set was mainly used to retrieve baseline characteristics to feed the propensity score model.
81. The endline survey captured information on all modules covered at baseline, plus additional outcome indicators following the EQs as well as a few background characteristics to be recalled from baseline to enrich the set of potential matching variables for the propensity score model.
82. Secondary data were additionally retrieved to control for district level geo-climatic characteristics in the endline analysis. These characteristics include average precipitation and temperature during the rainy seasons between October 2012 and May 2018.

D. QUALITY ASSURANCE AND VALIDATION OF DATA

83. The LORTA team together with the UNDP HQ team provided quality assurance throughout the entire evaluation process for the quantitative evaluation of PICSA. At baseline, the LORTA team engaged with UNDP, project stakeholders and the baseline survey firm during the LORTA country visit in September 2018. The LORTA and the UNDP teams developed the evaluation design and sampling strategy. Furthermore, the LORTA team provided feedback to the baseline questionnaire and baseline report. After the completion of the baseline report, the LORTA team refined the baseline data set. Some quality issues were encountered, as described above.

84. The LORTA team with support from UNDP redefined the evaluation strategy and developed a detailed data analysis plan to guide the endline quantitative evaluation, specifying the evaluation matrix, the sampling strategy, the IE method, the estimation strategy and variables for the expected analysis. In addition, the LORTA team also elaborated a detailed list of outcome variables and potential matching variables to capture in the endline survey.

85. At endline, the quality assurance of the evaluation proceeded through several stages, commencing with inception Zoom webinars, which were organized with UNDP, the LORTA team and the survey firm to reach a common ground of understanding of the assignment and to verify the baseline information against which this study compares outcomes**.** All developed tools (data analysis plan, list of outcome indicators and potential matching variables), as well as the baseline data set, sampling frame and secondary data, were shared with the endline survey firm to guide the evaluation.

86. A total of three webinar sessions were held with UNDP and the LORTA team before the endline survey firm was cleared for data collection. In all three sessions, major issues were resolved, especially those concerning identifying respondents and ensuring correspondence with the baseline sample.

87. Upon approval of the endline evaluation inception report, the survey firm identified a group of research assistants, who went through a five-day training before the field data collection. The training was aimed at enhancing the necessary skills and created a common understanding of the M-CLIMES project, the PICSA approach, the methodology, electronic data-collection targets, the practical use of survey equipment, and research ethics.

88. The LORTA team provided several rounds of feedback on the questionnaire. Once finalized, the endline survey firm pre-tested the questionnaire before the actual data collection as an integral part of the training. After the training, the endline survey firm piloted the programmed questionnaire using the tablets in Dedza district, one of the sampled districts, but in a different EPA. The endline survey firm organized a meeting to share experiences and analyse data from the pilot study. All emerging issues concerning the questionnaire were addressed before the field data collection. Both the training and pilot reports highlighting key issues and observations were submitted to UNDP.

89. The research team of the endline survey firm was organized into four teams. Each team comprised one consultant, one supervisor and six research assistants/enumerators. Each team was assigned two districts: one control district and one treatment district. All four teams started data collection with a treatment district, with the target to cover the treatment district in 10 days and the control district in 9 days, with a provision for revisiting households if necessary.

90. The endline questionnaire, the list of matching variables and the indicators were revised by the endline survey firm in close collaboration with UNDP and the LORTA team. The endline survey firm monitored the quality of the data collected via supervisors, who conducted routine data checks on the questionnaires completed by enumerators during the survey. In addition, daily feedback

sessions with consultants, supervisors and enumerators were conducted in the evening each day after returning from the field, to share challenges and observations, among other things, and agree on ways of addressing them. Similarly, UNDP was kept aware of any observations/challenges requiring their attention.

91. Data analysis and report writing were performed by the endline survey firm in close collaboration with the LORTA team. A series of data quality checks were performed before the final approval to proceed with data analysis. For example, the LORTA team advised on topics such as how to treat missing values, conduct logical checks, check for duplicates in the data, label variables, treat extreme values, recode “other, specify” values, merge data sets, generate clusters, and generate outcome variables. Several do-files for various tasks – including data cleaning, merging data sets, generating/creating outcome variables – were reviewed or produced by the LORTA team. At the end of the contract with the endline survey firm, the LORTA team finalized the revision of the construction of the data set (addressed unresolved merging issues, restructured do-files), and implemented all remaining unresolved data cleaning (relating variables’ generation and winsorization) and generated the final sample. The analysis presented in this report was performed by the LORTA team.

E. Ethics

92. All ethical considerations were adhered to throughout the study activities. Before fieldwork, the survey firms committed to training all research assistants in ethics in research involving human subjects. This was to ensure that the research team adhered to the following core principles of research, among others:

1) Obtaining informed consent from research participants
2) Minimizing the risk of harm to participants
3) Protecting their anonymity and confidentiality
4) Avoiding using deceptive practices
5) Giving participants the right to withdraw from the evaluation

93. The material used for training was shared with UNDP by the relevant survey firm before starting fieldwork. It constituted one of their deliverables. Electronic data-collection survey instruments were developed and deployed in the field on tablets. Consent was recorded for all survey respondents. Respondents were made aware of the nature of the evaluation and how their data would be used. For instance, pseudonyms were used and any identifiers (personal information) were removed.[18]

F. Software and code

94. MS Excel was used for drafting the questionnaires, and Open Data Kit (ODK) was used to programme baseline and endline surveys. ArcGIS was used to help visualize the locations of the project areas and check whether control and treatment farmer households resided in Malawi and in the selected the evaluation districts. Finally, Stata was used for statistical analysis.

[18] For the recordings made during key informant interviews and focus group discussions, consent was sought from the participants, and there were no identifiers in the whole discussion for confidentiality purposes.

Table IV-3. List of software used in the impact evaluation

Software	Purpose	Project objects derived
MS Excel	Cleaning the sampled baseline farmer listing of farm households Programming the household questionnaire to feed into ODK	Cleaned baseline farmer listing, programmed version of the endline questionnaire Codebook, a raw data set
ODK	Electronic and mobile data collection	Raw data sets
Stata	Data cleaning, management and statistical analysis	Do-files, log files, raw data set, cleaned data sets
ArcGIS	Generating maps	Maps showing IE districts and municipalities, heat maps

Source: CIE report

V. PRESENTATION OF RESULTS

A. MATCHING VARIABLES SUMMARY STATISTICS

95. In Table V-1 we present summary statistics for the matching characteristics of the PICSA participants and non-participants chosen for the propensity score model. About 78 per cent of the LF household heads are male, with an average age of 45, and an average household size of six members. Just over half (58 per cent) completed basic primary education. The overwhelming majority of LF households have access to cell phones (91 per cent) and electricity (81 per cent).

96. In terms of dwelling characteristics, 71 per cent of LF households have iron sheet roofing. Above 90 per cent of farmer households have brick or concrete walls, and improved water sources, based on the WHO classification. Owned land size ranges from 0.5 to 8.7 hectares, with an average size of 2.3 hectares. This is slightly more than the national average of 1.3 hectares per household found by the Food and Agriculture Organization (2015). Finally, 89 per cent of households donate to a church or a mosque, and 83 per cent of the households obtain income from keeping livestock.

97. Each LF has on average 20 CFs. This indicator ranges from 0 to 54 CFs. The number of field visits per LF ranges from 0 to 60, with an average value of 7 visits per year. The average village distance to the agricultural market is 6 kilometres.

98. The municipality-level average temperature over the rainy seasons during 2012–2018 varies between 20°C and 27°C, with an average of 23°C. The municipality-level average total precipitation over the 2012–2018 rainy seasons varies between 93 and 159 mm, with an average of 118 mm. Finally, the municipality-level elevation varies substantially, with a minimum value of 66 metres and a maximum value of 1,580 metres. The average value for this variable is 416 metres.

Table V-1. Descriptive statistics of matching variables

VARIABLE	OBS.	MEAN	STD. DEV.	MIN.	MAX.
Gender of household head	370	.778	.416	0	1
Age of household head	370	45.4	11.303	22	79
Household size	370	5.9	1.958	1	16
Household head completed primary school	370	.573	.495	0	1
Access to cell phone	370	.914	.281	0	1
Access to electricity	370	.814	.39	0	1
Iron sheet roofing	370	.711	.454	0	1
Brick/concrete walls	370	.927	.26	0	1
Improved water source	370	.908	.289	0	1
Owned land size	370	2.3	1.611	.5	8.649
Church/mosque contribution	329	7.5	1.287	4.615	11.067
Livestock income source	370	.822	.383	0	1
Number of CFs for each LF	358	20.6	14.571	0	54
Number of field visits	358	6.885	7.845	0	60
Village avg. distance to market (km)	370	6.108	8.463	0	76

VARIABLE	OBS.	MEAN	STD. DEV.	MIN.	MAX.
Municipality avg. temperature (°C) during rainy seasons 2012–2018	370	22.9	1.732	19.571	27.006
Municipality avg. precipitation (mm) during rainy seasons 2012–2018	370	118.3	20.244	93.706	159.11
Municipality avg. elevation (m)	370	988.7	416.279	65.936	1580.231

B. BALANCE TESTS BEFORE MATCHING

99. Table V-2 illustrates the balance tests between the key characteristics of the treatment and control LFs before matching. A number of indicators, especially the geo-climatic characteristics, significantly differed between the two groups before matching. The two indicators with differences that became more significant after matching are those for completed primary school education and if the house has brick or concrete walls. These differences are significant at the 10 per cent and 5 per cent levels, respectively. We find that these differences do not alter the matching models, and we keep them in the analysis.

Table V-2. Balance tests before matching

VARIABLE	TREATMENT (T) MEAN	COMPARISON (C) MEAN	T-TEST MEAN DIFFERENCE (T-C)	N OF OBS. (T)	N OF OBS. (C)
Gender of household head	0.779	0.778	0.001	154	216
Age of household head	45.3	45.4	-0.102	154	216
Household size	5.9	5.8	0.047	154	216
Household head completed primary school	0.578	0.569	0.008	154	216
Access to cell phone	0.903	0.921	-0.019	154	216
Access to electricity	0.799	0.824	-0.025	154	216
Iron sheet roofing	0.760	0.676	0.084*	154	216
Brick/concrete walls	0.942	0.917	0.025	154	216
Improved water source	0.896	0.917	-0.021	154	216
Owned land size	2.5	2.2	0.334**	154	216
Church/mosque contribution	7.7	7.4	0.334***	146	183
Livestock income source	0.857	0.796	0.061	154	216
Number of CFs for each LF	15.6	24.4	-8.8***	154	204
Number of field visits	5.7	7.7	-2.0***	154	204
Village avg. distance to market (km)	6.5	5.9	0.613	154	216
Municipality avg. temperature (°C) during rainy seasons 2012–2018	23.7	22.4	1.4***	154	216

VARIABLE	TREATMENT (T) MEAN	COMPARISON (C) MEAN	T-TEST MEAN DIFFERENCE (T-C)	N OF OBS. (T)	N OF OBS. (C)
Municipality avg. precipitation (mm) during rainy seasons 2012–2018	111.6	123.1	-11.5***	154	216
Municipality avg. elevation (m)	840.4	1094.5	-254.1***	154	216

Note: Columns 1 and 2 display the mean values of the matching variables for the treatment and control group, respectively. Column 3 shows t-tests for the differences in mean values between treatment and control groups. Significance levels are indicated by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C. PROBABILITY OF PARTICIPATION IN PICSA

100. The basic idea of matching is to compare a beneficiary with one or more non-beneficiaries who are similar in terms of a set of observed characteristics. This requires predicting the probability of participation in the programme – that is, the propensity score – for each individual. We estimate the propensity score using a logit model.

101. The dependent variable in the model is participation in the PICSA programme. It takes the value of 1 if an LF participates in the programme and 0 otherwise. Table V-3 shows the estimated marginal effects for the matching variables.

Table V-3. Propensity score model

DEPENDENT VARIABLE: TREATMENT DUMMY	COEFF.	S.E.	Z
Gender of household head	-0.025	0.059	-0.43
Age of household head	-0.003	0.002	-1.23
Household size	-0.002	0.012	-0.13
Household head completed primary school	0.013	0.053	0.26
Access to cell phone	-0.037	0.089	-0.41
Access to electricity	-0.029	0.068	-0.42
Iron sheet roofing	0.105*	0.061	1.72
Brick/concrete walls	-0.071	0.101	-0.71
Improved water source	-0.037	0.085	-0.44
Owned land size	0.009	0.016	0.58
Church/mosque contribution	0.036*	0.019	1.89
Livestock income source	0.080	0.069	1.16
Number of CFs for each LF	-0.009***	0.002	-4.93
Number of field visits	-0.006	0.004	-1.62
Village avg. distance to market (km)	0.003	0.003	0.98
Municipality avg. temperature (°C) during rainy seasons 2012–2018	0.053**	0.025	2.13
Municipality avg. precipitation (mm) during rainy seasons 2012–2018	-0.005***	0.001	-3.44

Dependent variable: treatment dummy	Coeff.	S.E.	z
Municipality avg. elevation (m)	-0.0001	0.0001	-1.24
Observations			317
Pseudo R^2			0.22
LR Chi^2			95***

Note: We use a logit model. The dependent variable is a binary indicator, equal to 1 for LFs in PICSA districts who participated in any PICSA trainings, 0 for LFs in non-PICSA districts. Column 2 shows estimated coefficients, column 3 shows standard errors and column 4 shows the corresponding Z-statistics. Significance levels are indicated by *** p<.01, ** p<.05, * p<.1.
LR: likelihood ratio

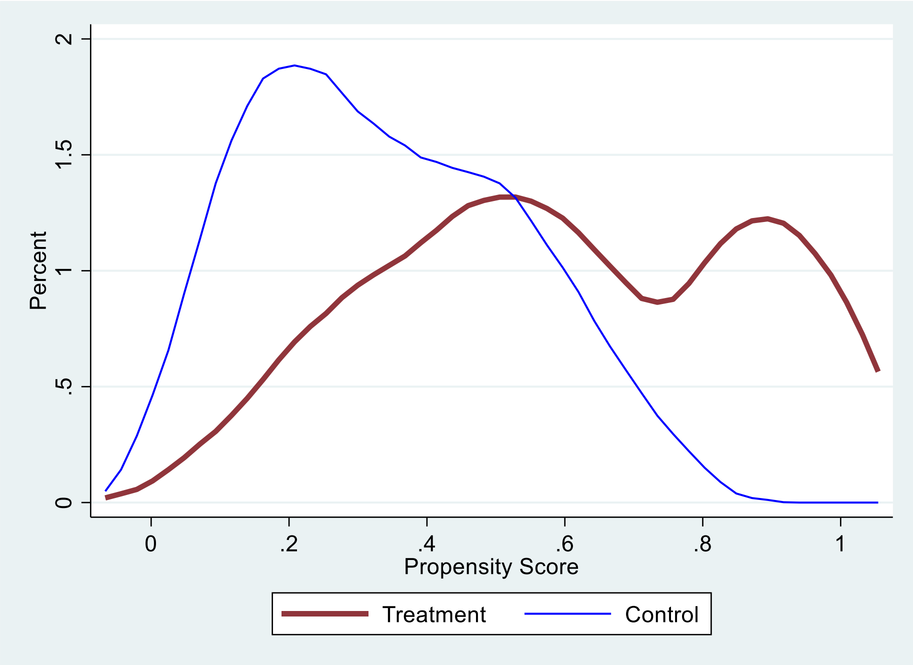
102. As indicated in Table V-3, iron sheet roofing and religious contributions, as proxies for wealth, had a significant and positive impact on participation in PICSA. We also see that LFs with relatively fewer CFs were selected for PICSA, which could be an indication of better coverage in terms of extension services in the treatment areas as compared to the control areas that were sampled. Geo-climatic characteristics control for between-municipality variation and the probability that the LF household is exposed to a weather shock based on past trends.

103. The pseudo R2 indicates that the matching variables are able to explain 22 per cent of the variation in PICSA participation. The LR Chi^2 shows that the matching variables are jointly significant. The estimated mean propensity score using the main specification for the whole sample was 0.42, implying that the average probability of participating in the PICSA programme for all the LFs is 42 per cent.

D. Common support

104. Figure V-1**Error! Reference source not found.** presents the distributions of the propensity scores for LFs in the treatment (red colour) and control groups (blue colour). As expected, the distribution of the propensity scores of the treatment group is skewed in the opposite direction with respect to the control group. Overall, there is a considerable overlap in the propensity scores between the two groups (common support).

Figure V-1. Distribution of the propensity scores



E. DESCRIPTIVE STATISTICS

1. Output and short-term outcome indicators

105. In this section, we present the descriptive statistics of some key outputs and short-term outcome indicators.

Outputs

106. As per the ToC, trainings were planned for LFs in PICSA districts. In parallel, the M-CLIMES project had planned to deliver agricultural recommendations via SMS to the LFs. We therefore investigate the extent of the implementation of these interventions in the PICSA districts using information reported by LFs. In the PICSA districts, 92 per cent (163) of the 178 LFs reported having attended at least one PICSA training. Over half of the LFs (139) attended the PICSA training in October 2018 and over 40 per cent (102) attended the PICSA refresher training in June 2019.

107. Furthermore, 23 per cent of LFs reported having received agricultural recommendations via SMS during the 2019 rainy season. This share lowers to 18 per cent among LFs who attended any PICSA training. As described in section 0C, the implementation stage for the delivery of agricultural recommendations is still at a relatively early stage.

Table V-4. Descriptive statistics of outputs for lead farmers in the treatment group, EQ1

Indicators	Obs.	Mean	Std. dev.	Min.	Max.
Attended any PICSA training	178	0.916	0.279	0	1
Attended 2018 PICSA training	242	0.574	0.495	0	1
Attended 2019 PICSA refresher training	242	0.421	0.495	0	1
Received agricultural recommendations via SMS during rainy season 2019	271	0.232	0.423	0	1

Note: For each indicator; column 1 displays the number of observations; column 2 displays the mean value; column 3 displays the standard deviation; columns 4 and 5 display the minimum and maximum values.

Short-term outcomes

108. In the following part of the analysis, we restrict the focus to describing outcomes for the 397 LFs in the treatment and control groups. As can be seen from the low number of observations, these indicators have a large number of missing values.

109. Overall, 75 per cent of the LF households that responded to the survey accessed the rainfall seasonal forecasts for the 2019 rainy season. The primary source of information was radio (48 per cent), followed by the government extension workers (36 per cent), SMS (12 per cent), and friends, relatives or other individuals (4 per cent). Out of those who accessed seasonal forecasts, the majority (64 per cent) recalled that the seasonal forecasts indicated the rainfall onset dates, 14 per cent recalled that they indicated the rainfall cessation dates and 8 per cent recalled that they indicated rainfall distribution per month. Around a half of LF households indicated that the seasonal rainfall forecasts included information for their districts, and 64 per cent indicated the presence of a map. Almost every household (95 per cent) indicated that the forecasts were timely. In terms of short-term rainfall forecasts, out of those who answered 63 per cent of the LF households reported that they had access to them. Of these, 56 per cent relied on information from the radio, 25 per cent accessed the warnings through the government extension workers, 12 per cent through SMS/phone, and 7 per cent through friends, relatives or other individuals.

Table V-5. Descriptive statistics for short-term outcomes, EQ3

Indicators	Obs.	Mean	Std. dev.	Min.	Max.
Accessed seasonal rainfall forecasts in 2019 rainy season	198	0.747	0.436	0	198
The primary source of seasonal rainfall forecasts in the 2019 rainy season					
Government extension workers	148	0.358	0.481	0	1
Radio	148	0.480	0.501	0	1
SMS /phone	148	0.122	0.328	0	1
Friends, relatives, others	148	0.041	0.198	0	1
Type of information included in seasonal forecasts					
Dates on rainfall onset	148	0.635	0.483	0	1
Dates on rainfall cessation	148	0.122	0.328	0	1
Rainfall distribution per month	148	0.081	0.274	0	1

INDICATORS	OBS.	MEAN	STD. DEV.	MIN.	MAX.
Seasonal forecasts 2019 rainy season included information for own district	148	0.493	0.502	0	148
Seasonal forecasts in 2019 rainy season included maps	148	0.642	0.481	0	1
Accessed seasonal rainfall forecast for 2019 rainy season in time for use	148	0.946	0.227	0	1
Accessed short-term rainfall warnings in rainy season 2019	198	0.631	0.484	0	1
The primary source of short-term rainfall forecasts in the 2019 rainy season					
Government extension workers	125	0.248	0.434	0	1
Radio	125	0.560	0.498	0	1
SMS/phone	125	0.120	0.326	0	1
Friends, relatives, others	125	0.072	0.259	0	1

Note: For each indicator; column 1 displays the number of observations; column 2 displays the mean value; column 3 displays the standard deviation; columns 4 and 5 display the minimum and maximum values.

2. Intermediate and long-term outcome indicators

110. In this section, we present the summary statistics for the intermediate and long-term outcomes. Table V-6 displays the summary statistics for the overall sample, Table V-7 shows the statistics by gender of the household head and Table V-8 compares statistics between treatment and control group.

111. As shown in Table V-6, at endline only 5 per cent of LFs report that they use seasonal forecasts to plan farm decisions, but 27 per cent of LFs report that they use seasonal forecasts to make crop variety choices. More generally and irrespective of seasonal forecasts, around 45 per cent made changes to crop activity during the last rainy season. The average number of crops grown per LF is about three.

112. For livestock activities, around 18 per cent of farmers reported having made changes (starting a new livestock enterprise, increasing or decreasing the scale of an existing livestock enterprise).

Table V-6. Descriptive statistics of intermediate and long-term outcome indicators

EQ	INDICATORS	OBS.	MEAN	STD. DEV.	MIN.	MAX.
Intermediate outcomes						
4	Used seasonal forecasts to plan farm decisions in 2019 rainy season	370	.054	.226	0	1
4	Used seasonal forecasts to make crop variety choices in 2019 rainy season	370	.265	.442	0	1
4	Made changes to crop activity in 2019 rainy season	370	.451	.498	0	1
4	Number of crops grown in 2019 rainy season	370	2.8	1.2	1	11
4	Made changes to livestock activity in 2019 rainy season	370	.181	.386	0	1

EQ	INDICATORS	OBS.	MEAN	STD. DEV.	MIN.	MAX.
						Long-term outcomes
5	Maize yield (kg/ha) in 2019 rainy season	342	867.6	1083.7	25	12,000
6	*Ganyu* income source	370	.249	.433	0	1
7	Worried about food shortage	370	.384	.487	0	1
7	Ln of food expenditures	370	9.2	1.2	0	11.29

Note: For each indicator; column 1 displays the number of observations; column 2 displays the mean value; column 3 displays the standard deviation; columns 4 and 5 display the minimum and maximum values.

113. In terms of long-term outcomes, the average maize yield is 881 kg/ha. In contrast, the national average is a bit more than 2,000 kg/ha, which can be explained by the inclusion of estates on leasehold and freehold land within this figure. The survey value for smallholders on customary land is almost half of the national average.

114. Finally, moving to food security, around 38 per cent of the households worry about food shortage. The average value of food expenditures per month for a household in our sample is 15,188 Malawian kwachas, which is equivalent to a bit less than the current USD 20 per month (using spot exchange rates from 2020). The maximum value in the sample is 662,500 Malawian kwachas, which is USD 813 a month. Finally, around 25 per cent of the LFs reported that they work on the farms of others as a secondary source of income (*ganyu*).

115. When disaggregating summary statistics by the gender of the household head (Table V-7), we observe that LFs in male-headed households are more likely to report to have made use of seasonal forecasts to plan farm decisions (M: 5.9 per cent; F: 3.7 per cent) and make crop variety choices (M: 27.8 per cent; F: 22 per cent). However, male-headed households are less likely to report changes in either crop (M: 44.1 per cent; F: 48.8 per cent) or livestock (M: 16.3 per cent; F: 24.4 per cent) activities.

116. The average number of cultivated crops per farmer is slightly less than three in both groups. Maize yields reported by LFs are lower for male- as compared to female-headed households (M: 831.7 kg/ha; F: 1004.6 kg/ha). Although female-headed households seem to worry less about food shortage (M: 36.8 per cent; M: 43.9 per cent), their average food expenditure is lower than that of male-headed households (M: 9.2; F: 8.9), possibly reflecting a greater reliance on subsistence production. Finally, LFs in female-headed households are more likely to report working on the farms of others (M: 23.6 per cent; F: 29.3 per cent).

Table V-7. Descriptive statistics of intermediate and long-term outcome indicators, by gender

EQ	INDICATORS	MALE (M) OBS.	MALE (M) MEAN	FEMALE (F) OBS.	FEMALE (F) MEAN
Intermediate outcomes					
4	Used seasonal forecasts to plan farm decisions in 2019 rainy season	288	.059	82	.037
4	Used seasonal forecasts to make crop variety choices in 2019 rainy season	288	.278	82	.22
4	Made changes to crop activity in 2019 rainy season	288	.441	82	.488

EQ	Indicators	Male (M) Obs.	Male (M) Mean	Female (F) Obs.	Female (F) Mean
4	Number of crops grown in 2019 rainy season	288	2.9	82	2.5
4	Made changes to livestock activity in 2019 rainy season	288	.163	82	.244
Long-term outcomes					
5	Maize yield (kg/ha) in 2019 rainy season	271	831.7	71	1004.6
6	*Ganyu* income source	288	.236	82	.293
7	Worried about food shortage	288	.368	82	.439
7	Ln of food expenditures	288	9.2	82	8.9

Note: For each indicator; columns 1 and 3 display the number of observations for the female-headed and male-headed LF households, respectively; columns 2 and 4 display respective mean values.

117. In Table V-8, we see that in general, the treatment group is better off for most outcomes than the control group. Specifically, a higher percentage of LFs relies on seasonal forecasts to plan farm decisions (T: 10.4 per cent; C: 1.9 per cent) and to make crop variety choices (T: 37.7 per cent; C: 18.5 per cent), made changes to crop activity (T: 62.3 per cent; C: 32.9 per cent) and livestock activity (T: 21.4 per cent; C: 15.7 per cent), as compared to the control group. Also, treated LFs exhibit higher yields compared to their peers in the control group (T: 1,012.8 kg/ha; C: 771.7 kg/ha). Finally, a lower percentage of treated LFs worry about food shortage (T: 28.6 per cent; C: 45.4 per cent) and work in the farms of other households (T: 18.8 per cent; C: 20.2 per cent), compared to LFs in the control group.

118. Nonetheless, descriptive results cannot explain whether the observed differences in the outcomes between the two groups of households are due to the programme or confounding factors.

119. Note that our results for the reported changes in crop and livestock activities from the PICSA LFs are lower than those reported in the PICSA monitoring and evaluation assessments conducted by Clarkson, Van Hulst and Dorward (2020) as part of the M-CLIMES project and lower than those reported by PICSA performance monitoring assessments in other countries (Clarkson and others, 2019).

120. In particular, Clarkson, Van Hulst and Dorward (2020) report that as of June 2019, 95 per cent of PICSA LFs reported making changes to their crop activities, 31 per cent of LFs reported making changes to their livestock activities and 7 per cent of LFs reported making changes to their livelihood activities. However, it is important to note that – while the assessment of Clarkson, Van Hulst and Dorward (2020) was conducted seven months after the implementation of the PICSA trainings – our evaluation referred to the 2019 rainy season – that is, one year after the first PICSA trainings.

Table V-8. Descriptive statistics of intermediate and long-term outcome indicators, by treatment status

EQ	Indicators	Treatment (T) obs.	Treatment (T) mean	Control (C) obs.	Control (C) mean
Intermediate outcomes					
4	Used seasonal forecasts to plan farm decisions in 2019 rainy season	154	.104	216	.019
4	Used seasonal forecasts to make crop variety choices in 2019 rainy season	154	.377	216	.185
4	Made changes to crop activity in 2019 rainy season	154	.623	216	.329
4	Number of crops grown in 2019 rainy season	154	2.96	216	2.7
4	Made changes to livestock activity in 2019 rainy season	154	.214	216	.157
Long-term outcomes					
5	Maize yield (kg/ha) in 2019 rainy season	136	1012.8	206	771.7
6	*Ganyu* income source	154	.188	216	.292
7	Worried about food shortage	154	.286	216	.454
7	Ln of food expenditures	154	9.19	216	9.1

Note: For each indicator; columns 1 and 3 display the number of observations for the treatment and control LF households, respectively; columns 2 and 4 display respective mean values.

F. The impact of participation in PICSA

121. Using estimated propensity scores from the model specification in Table V-3, we estimate the impacts of PICSA on the selected intermediate and long-term outcomes. The results are presented in Table V-9. As described in section 0B2, we employ several algorithms: (1) 1-1 matching, (2) NN matching with two or six nearest neighbours considered, (3) radius matching with 0.2 caliper, and (4) kernel matching with 0.06 and 0.1 bandwidth. The respective estimated treatment effects are displayed in columns 1–6.

122. Column 7 displays ordinary least squares (OLS) estimates, showing the simple difference in endline values between outcomes for the treatment and control group (with imposed common support). Column 8 shows the average value of the outcomes for the control group.

123. Overall, the findings indicate that the PICSA intervention was successful in improving both intermediate and long-term outcomes.

1. Intermediate impacts

124. We detect a positive treatment effect of 4.5 to 6 percentage points (control group mean: 1.9 per cent) on the use of seasonal forecasts to plan farm decisions. However, this effect is significant for three matching algorithms out of six. We also find significant effects of PICSA on the use of seasonal forecasts to make crop variety choices. The estimate ranges from 14 to 17 percentage points (control group mean: 18.5 per cent).

125. Further, we find that the likelihood to make changes to crop activities increased by 25–36 percentage points (control group mean: 32.9 per cent). We do not find strong evidence that PICSA farmers increased the number of crops grown.

126. Unfortunately, we do not have information on whether the distribution of crops shifts between food and cash crops. While maize has been the major food crop in terms of the policy agenda and hectarage planted, tobacco has been and continues to be the dominant cash crop in the economy, accounting for over 50 per cent of the country's total export earnings. Tea and sugar are two further export crops but are mainly grown by smallholders on the fringes of estates as out-growers or contract farmers. In our survey, we find that before PICSA, 12 per cent of the households grew tobacco, and 4 per cent grew tobacco as the first crop.

127. We also do not find significant impacts on changes in livestock activities. Part of the PICSA trainings included recommendations on livestock husbandry practices, and it was expected that from these recommendations farmers would make necessary adaptations of the livestock activities. In our survey, the farmers breed chickens, goats, pigs and bulls. However, only 3.5 per cent of farmers receive income from breeding animals through sales. It is assumed that other farmers use livestock mostly for consumption. It may be the case that only the wealthiest households may make substantial changes to the livestock activities, as livestock is a typical wealth indicator for rural Malawi. It may also be the case that the majority of farmers received more detailed information from PICSA about changes in agricultural activity rather than livestock, because the majority of households sustain themselves on agriculture rather than livestock, both in our survey and in Malawi in general.

2. Long-term impacts

128. The estimated effects on yields range between 434 kg/ha and 505 kg/ha (Table V-9). This effect size is substantial when compared to the control group mean, representing an increase of almost 60 per cent. This finding largely diverges from the literature on the effect of smallholder farming interventions, such as farmer field schools where systematic review evidence reports an average impact of 13 per cent on yields (Waddington and others, 2014). When we compare this increase in maize yields to the trend in smallholder maize yields from 2002 to 2015 in Malawi, we note that the PICSA impact represents a broadly similar increase to that achieved over 13 years (see Prowse and Hillbom, 2018). We therefore need to be mindful of the possibility of substantial measurement error in this variable due to the self-reported nature of the data on yields.

129. We do not find statistically significant impacts on the food security indicators, either on the worry of food shortage or on food expenditures. It is very plausible that PICSA had impacts on certain farming decisions and food crops, such as maize, but has not increased food security (through increasing incomes, as most maize grown in Malawi is for consumption). Due to resource limitations, we cannot conduct a long-term survey (several years after PICSA implementation) to check for actual impacts on changes in food security.

130. Finally, we observe a statistically significant reduction in working on other farms (*ganyu*). As mentioned earlier, this is an indicator of poverty in Malawi, with mostly women engaged in this activity. The effect ranges from 9 to almost 16 percentage points.

131. As a robustness check across the models, we compare the following statistics: Rubin's B and Rubin's R. Rubin's B is the absolute standardized difference of the means of the linear index of the propensity score in the treated and (matched) non-treated group, and Rubin's R is the ratio of treated to (matched) non-treated variances of the propensity score index. Rubin (2001) recommends that B be less than 25 and that R be between 0.5 and 2 for the samples to be considered sufficiently balanced. A hash sign is displayed next to Rubin's B and Rubin's R values that fall outside those

limits in Table V-9. Two models perform better than others when comparing these statistics: NN (6), which utilizes more neighbours for matching than NN (2), and kernel matching with a bandwidth of 0.06.

Table V-9. Impact estimates for participation in PICSA trainings

	1-1 MATCHING	NN (2)	NN (6)	RADIUS MATCHING (0.2)	KERNEL BW (0.06)	KERNEL BW (0.1)	OLS	CONTROL ENDLINE MEAN
Intermediate outcomes								
Use of seasonal forecasts to plan farm decisions*†	.040 (.032)	.045 (.031)	.057** (.027)	.060* (.029)	.054 (.034)	.057* (.034)	.049* (.029)	.019
Use of seasonal forecasts to make crop variety choices*†	.172*** (.073)	.136* (.073)	.141** (.061)	.141*** (.060)	.136** (.064)	.135** (.060)	.142*** (.058)	.185
Any change to crop activities*†	.364*** (.084)	.323*** (.077)	.316*** (.067)	.295*** (.065)	.330*** (.066)	.323*** (.063)	.248*** (.063)	.329
Number of crops grown*	.111 (.207)	.141 (.170)	.271* (.164)	.299* (.165)	.147 (.154)	.138 (.147)	.289* (.163)	2.7
Any change to livestock activities*†	.061 (.068)	.040 (.052)	.008 (.052)	.006 (.052)	.035 (.060)	.031 (.057)	.009 (.050)	.157
Long-term outcomes								
Maize yield (kg/ha)*	504.5*** (164.3)	489.9*** (155.7)	502.6*** (164.3)	459.4*** (167.9)	433.9** (209.4)	444.7** (204.8)	439.5*** (171.2)	771.7
Ganyu income source†	-.162*** (.078)	-.136* (.073)	-.094* (.057)	-.096* (.053)	-.114** (.049)	-.125*** (.048)	-.130*** (.049)	.292
Worry of food shortage†	-.051 (.086)	-.061 (.077)	-.104 (.070)	-.098 (.065)	-.090 (.069)	-.092 (.067)	-.115 (.062)	.454
Ln of food expenditures	-.229 (.184)	-.206 (.178)	-.199 (.179)	-.203 (.174)	-.137 (.141)	-.140 (.139)	-.227 (.173)	9.1
Number of observations	260	260	260	260	269	269	256	
Rubin's B	49.5[#]	35[#]	24.6	26.2[#]	18	40.4[#]		
Rubin's R	0.76	1.21	0.92	1.29	1.13	1.28		

Notes: Indicators marked with * are measured with reference to the 2019 rainy season. Indicators marked with † are binary. For NN matching, standard errors are corrected based on Abadie and Imbens (2006, 2016). For kernel matching, bandwidth is 0.1 and 0.2, standard errors are bootstrapped (with 1,000 replications). Stata commands psmatch2 and kmatch were used for the estimations.

VI. DISCUSSION

132. Our results show that PICSA increases farmers' use of seasonal forecasts in agricultural decision-making and leads to positive changes in crop activities. The findings are aligned with the ToC, designed at the beginning of the intervention.

133. In particular, when comparing PICSA LFs to LFs in control districts, we find a 5 to 6 percentage point increase (control group mean: 1.9 per cent) in the likelihood to use seasonal forecasts to plan farm decisions and an increase of 14 to 17 percentage points in the likelihood to use seasonal forecasts to make crop variety decisions. We also find large and positive effects for the likelihood to make changes to crop activities (25 to 36 percentage points, control group mean: 32.9 per cent). PICSA also appears to provide benefits in terms of higher agricultural yields – for maize, in particular (434 to 505 kg/ha, control group mean: 771.7 kg/ha). Finally, we also find a significant negative effect of 9 to 16 percentage points (control group mean: 29.2 per cent) on the likelihood to work on the farms of others as a source of income (*ganyu*). Such changes can be seen as being responses to the participatory approach embedded in PICSA, the farming systems approach and use of both historical and forecast-based climate data to allow farmers to make choices under uncertainty.

134. We do not find an impact on food security. However, we measured the impacts two years after the first PICSA training took place for the LFs. While we find a positive impact on intermediate and long-term outcomes, we do not know whether these effects will be sustained in the long run or will meet the overall goal of enhanced farmers' resilience against climate change. A longer evaluation time frame and a more complex approach would be necessary in order to assess such impacts. Furthermore, whether a two-year period is sufficient to see impacts on long-term indicators such as food security is debatable. We also acknowledge that these results represent the treatment on the treated estimates, which means that these are the impacts that we observe on those farmers who systematically attended PICSA. If we explore the results for those farmers who were offered the training but did not attend, we may find less significant changes. We cannot, however, explore this due to data limitations and lack of information on the take-up and drop-outs.

135. It is important to highlight that such interventions could be seen as being a "drop in the ocean" without addressing institutional and social challenges. For example, qualitative observations showed that illiteracy could be a large challenge in grasping PICSA recommendations. While a little over half of the farmers surveyed completed primary school, almost all LFs were literate. Scaling up PICSA may require adapting the programme for an illiterate population in a considerable way.

136. Another important challenge to consider in future implementations of PICSA and similar interventions is highlighted by Andersen (2019). The author found that government extension services in Malawi face major challenges: the number of extension workers has been falling, and the government is unable to fill most vacant positions due to limited resources. Around 70 per cent of the positions at the EPA level are vacant. Therefore, targeting AEDOs may not be the best approach for the sustainability of interventions such as PICSA. The LF extension model, as implemented by the government and various NGOs, has the potential to assist in bridging the gap, but it cannot replace the extension workers.

137. The endline survey firms observed that some subject matter specialists from the crop, veterinary, fisheries and land resource departments were not involved in PICSA activities at the district level. Incorporating specialists may help to provide expertise on crop and livestock requirements before farmers choose their options based on context. The endline survey firm also experienced limited cooperation from some of the extension officers, which impacted the survey.

138. Finally, the majority of farmers in Malawi are CFs, and the PICSA intervention we evaluated did not directly involve CFs during training due to a number of implementation challenges, including capacity constraints for the implementing agencies.

139. The assumption that LFs would understand the PICSA content from AEDOs and hence pass it on to CFs is ambitious. When communication channels become longer, critical information is lost as it moves from one person to another. For instance, the endline survey firm reported that, in all districts, the short-term weather information generated on daily basis did not seem to reach the CFs in the villages.

140. These challenges and limitations provide a solid basis for learning, not only in PICSA implementation and scale-up but also in future evaluations of similar interventions.

Agricultural and adaptation policy in Malawi

141. We now locate the PICSA intervention within the agricultural and adaptation policy landscape in Malawi before concluding the report. Since the late 1990s, the Government of Malawi and donors have implemented an agricultural policy in Malawi based on different forms of fertilizer subsidy schemes, starting with the Starter Pack scheme in 1998, which subsequently evolved into a “targeted” social safety net in the form of a targeted input programme. Following food security crises in 2001/2 and 2005/6, a voucher-based fertilizer subsidy scheme was implemented nationally, which doubled annual maize production from 1.2 million to 2.6 million metric tons. Until the 2013/14 season, maize production only dropped below 3 million metric tons once, in 2007/8 (Chirwa and Dorward 2013, Arndt and others, 2016). In parallel, tobacco, sugar and tea commodity chains in the country experienced a rapid expansion of contract farming and out-grower schemes, leading to the development of a contract farming strategy and a greater role for the Competition and Fair Trading Commission in regulating this form of exchange (Prowse and Grassin, 2020) Despite maintaining national-level food security, the role of the fertilizer subsidy schemes in Malawi has been contentious: the schemes have been seen to be inefficient, to crowd out the private sector and to create an unsustainable drain on fiscal resources.

142. The IEU’s (forthcoming) evaluation on the GCF’s investments and approach in the least developed countries features a case study on Malawi that highlights how the PICSA project dovetails well with national adaptation and development priorities. The Malawi national adaptation programme of action identified agriculture and fisheries as two of the top three sectors in terms of vulnerability to the impacts of climate change. Moreover, climate information services in agriculture are firmly embedded in the country’s wider adaptation policy framework, including the national adaptation plan, the Malawi Growth and Development Strategy (versions I, II and III), the National Resilience Strategy, and the intended nationally determined contributions. For example, the Malawi Growth and Development Strategy II highlights the importance of improved weather and climate monitoring for early warning and response. This national development planning document suggests that people-centred, integrated EWS, including community-based EWS, are a national priority – precisely the intervention that PICSA has delivered (Malawi, 2017). In addition, the second component of the National Resilience Strategy (2018–2030) also highlights the importance of early warning and response systems and of increasing productivity in the Malawian context (Malawi, 2018). The PICSA approach also dovetails closely with the forthcoming National Framework for Climate Services.

143. Our findings that PICSA had a statistically significant and positive impact in building adaptation capacity for LFs through greater use of seasonal forecasts, changes in crop activity, a greater focus on their farms and a dramatic increase in maize yields, suggests that the approach is able to support farmers facing the risks of climate change and climate variability. In particular, it showcases a way

through which maize yields and adaptive capacity can be increased, which complements the existing policy approach of voucher-driven fertilizer subsidies.

VII. CONCLUSION

144. PICSA is a training-based intervention seeking to empower farmers in making informed agricultural and livelihood decisions based on accurate, location-specific climate and weather information and the use of tools for participatory discussions. Training is delivered through a ToT approach, where extension officers are first trained and are then responsible for leading training sessions of LFs. These trainings were conducted in 2018 and 2019 in the districts of Chikwawa, Dedza, Ntcheu and Rumphi in rural Malawi. Before the trainings, a baseline survey was conducted of the potential participants of the intervention to record initial data on the variables of interest on the beneficiaries of PICSA in the targeted districts. For comparison, other farmers from the Phalombe, Lilongwe, Dowa and Mzimba districts were also interviewed in the same year as the control group. In 2020, we conducted the endline survey on the same farmers who were interviewed in 2018.

145. The evaluation was aimed at exploring the impact of the PICSA intervention on several levels, following the ToC. First, it examined whether the implementation of PICSA occurred as planned in terms of training participation. Second, in terms of short-term outcomes, was whether PICSA LFs accessed seasonal and weather forecasts for rainfall. Third, the evaluation aimed at estimating the causal effects of PICSA on both intermediary and long-term outcomes, which included the use of seasonal forecasts for farming decisions, making crop and livestock adaptations, crop yields, and food security outcomes.

146. The overall quantitative findings were complemented by qualitative interviews and observations collected during the endline survey.

147. Overall, the impact analysis shows that PICSA yields positive results on both intermediary and long-term outcomes. In particular, the evaluation found significant and robust positive impacts on the use of seasonal forecasts to plan farm decisions, changes to crop activity, maize yields, and an increase in well-being in terms of a reduction in work on other farms (*ganyu*).

148. Implementation and evaluation challenges and limitations highlighted through the report and discussed in previous sections should be kept in mind when assessing the conclusions of our study.

POLICY IMPLICATIONS

149. Based on the results from the evaluation, the following policy implications can be drawn on to improve the design and implementation of PICSA and similar interventions:

1) There is a need to enhance access to climate and weather information through various communication channels such as radio, television and other digital means, especially during the COVID-19 pandemic when printing posters and delivering them from central areas to peripheries may not be practical. Collaboration with community leaders and various community radio stations could be strengthened to reach a wider community of farmers with locally relevant climate information.
2) PICSA is a relatively short-term intervention, and its sustainability is unclear. It is therefore important that refresher meetings of a similar nature are held more regularly to enhance learning, mobilize knowledge exchange between LFs and CFs, and impact their decision-making.
3) Due to the limited number of AEDOs across the country, another training approach could be taken. Training LFs directly may prove to be more effective and would reduce the length of the knowledge exchange chain, thereby reducing the loss of information and potentially reaching a larger group of CFs.

150. More broadly, the IE report raises the following suggestions for policymakers in Malawi:

1) The PICSA approach to empowering farmers in making informed agricultural decisions based on accurate, location-specific climate and weather information and participatory discussions can complement existing policies to enhance adaptive capacity and maintain national-level food security.
2) Scaling up PICSA needs to include a rigorous IE component to ensure that the impact can be measured with accuracy overall and by relevant subgroups. Furthermore, to ascertain the sustainability of impact on shorter-term outcomes and the impact on longer-term outcomes, a longer time frame should be considered for an evaluation.

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APPENDICES

Appendix 1. QUALITATIVE METHODOLOGY

As part of the mixed-method study, qualitative data were gathered at endline to complement the quantitative findings with insights on how PICSA is implemented, the challenges, the gender dynamics and the sustainability of PICSA.[19]

The tools employed were key informant interviews and focus group discussions. The qualitative sampling strategy for interviews applied a purposive sampling approach. Interviews were conducted at national, district and EPA levels, taking into account gender dynamics. At the national level, interviews were conducted with PICSA implementing partners and responsible partners – namely, DAES, NASFAM, DoDMA, Department of Fisheries and Department of Water Resources, M-CLIMES Project Coordination Unit, Environmental Affairs Department, and DCCMS. Interviews were also conducted with the World Food Programme (WFP) staff members, who are also implementing the PICSA approach in some districts, some of which are M-CLIMES target districts. The aim was to validate and cross-check how WFP embraced the PICSA approach in their interventions and the impacts thereof. At the district level, interviews were conducted with subject matter specialists at the district agricultural office, AEDOs, district responsible partners' staff and other district sector specialists. At the community level, interviews were conducted with agricultural extension development coordinators and AEDOs as well as NASFAM field officers.

A total of 16 focus group discussions were conducted with farmers on the ground in the EPAs, with gender dynamics considered. Two focus group discussions were conducted in each district (both control and treatment), with groups of male and female farmers meeting separately. Each focus group discussion had a maximum of 10 participants.

The qualitative analysis was conducted through various approaches:

- Content analysis: reducing large amounts of unstructured textual content into manageable data relevant to the evaluation questions
- Thematic coding: recording or identifying passages of text or images linked by a common theme or idea, allowing the indexation of text into categories
- Narratives: construction of coherent narratives of the changes occurring for an individual, a community, a site, or a programme or policy
- Timelines: a list of key events, ordered chronologically

[19] Qualitative data were also collected at the baseline by another survey firm. The design of the survey and the target groups were very different from the endline and were used to inform project implementation – namely, EWS in general (e.g. the need to use local language in warnings, to include maps, indicate risks). Therefore, these results are not triangulated with endline qualitative and quantitative findings.

Appendix 2. Sample distribution at baseline

Table A - 1 shows the distribution of CFs by farmer clusters as per the baseline data for the sample of farmers for whom the LF–CF relationships are observed. For this reason, we refer to complete clusters.

Table A - 1. Number of contact farmers per complete cluster at baseline

Group	#of Clusters	Min.	Mean	Max.
Control	215	1	2.66	7
Treatment	162	1	2.43	7

Source: LORTA team
Note: One cluster is defined as complete if it comprises one LF plus any of his or her CFs.

Appendix 3. POWER CALCULATIONS AND BASELINE SAMPLE SIZE

The sample size targeted at baseline was informed by power calculations performed by the LORTA team. Power calculations broadly refer to a set of formulas used to compute the minimum sample size required to detect the impacts of a project in an experimental set-up.

The team used the following power formula for clustered randomization designs that relates the sample size to the minimum detectable effect size (MDES) (i.e. the expected difference in mean outcomes between the treatment and comparison groups):

$$MDES = (t_{1-\kappa} + t_{\alpha})\sqrt{\frac{1}{P(1-P)}}\sqrt{1+ICC(m-1)}\sqrt{\frac{\sigma^2}{N}}\sqrt{1-R^2}$$

where $t_{1-\kappa}$ and t_{α} are t-statistics representing the required power and level of statistical significance (by convention, we seek the power of 80 per cent[20] and a statistical significance of 5 per cent[21]), P represents the proportion in one of the two compared groups (allocation ratio), ICC is the intra-cluster correlation,[22] m is the number of households per cluster (one LF plus his or her CFs), σ^2 is the variance of the outcome variable of interest, N is the total sample size, and R^2 represents the extent to which baseline characteristics predict the endline outcome variable.

The key outcome of interest is maize yields. Descriptive statistics for maize yields have been obtained from previous studies (e.g. Komarek and others, 2017), as follows:

- The mean yield for maize is 1.8 t/ha.
- The standard deviation is 1.17 t/ha.
- An ICC of 15 per cent, based on similar studies in other countries on agriculture extension services (BenYishay and Mushfiq Mobarak, 2018).[23]

Based on different studies on the benefit of climate information, we expected that PICSA trainings would lead to increased productivity and higher yields for the treated farmers. In a study of seasonal climate forecasts and participatory workshops for smallholder farmers in four villages in Zimbabwe, Patt, Suarez and Gwata (2005) observed that farmers who reported changing their management based on forecast information experienced a 19 per cent yield benefit in 2003/04, and a 9 per cent benefit averaged across years, relative to farmers who did not respond to forecast information. Studies with extended interactions between farmers and institutions that provide EWS information have been shown to have reasonably high rates of use and benefits (Hansen and others, 2011). Roncoli and colleagues (2009) state that farmers reported higher yields based on participatory EWS information received and that they were better prepared for the planting season.

We expected PICSA to have a yield impact of at least 10 per cent within two years. In other words, at endline, we expected to observe a difference between the average yield of treated farmers and the

[20] This is the probability of correctly concluding that an intervention has an effect. It is commonly set at 80 per cent in social sciences.
[21] This is the probability of a false-positive result: the chance that a result shows that a treatment has an impact when in reality it does not. A broadly accepted threshold in the impact evaluation literature is 5 per cent.
[22] It is important to account for clustering when performing power calculations. The reason is that we expect the behaviours and hence the outcomes of beneficiaries (and non-beneficiaries) to be significantly correlated when they belong to the same cluster. This phenomenon is measured by the ICC: the higher the ICC, the lower the informational value of an extra observation from the same cluster. In other words, the ICC (that exists because of clustering) depreciates information, and this depreciation must be compensated for by either increasing the sample size, accepting a lower statistical precision, or considering a larger treatment effect size.
[23] Also, baseline data from an unpublished C4ED project on Integrated Soil Fertility Management in Burkina Faso.

average yield of control farmers to be at least 0.18 t/ha, which corresponds to a 10 per cent change from a baseline yield of 1.8 t/ha. The standardized MDES is expressed in terms of the number of standard deviations and is calculated below:

$$Standardized\ MDES\ = \frac{MDES}{SD} = \frac{0.18}{0.17} = 0.15\ SD$$

The power calculations were performed on the pooled sample of farmers (LFs + CFs). The allocation ratio was set at 50:50. While the standard practice is to oversample the control group, an equal sample split was decided at the time in agreement with the project team to allow for enough sample size in the treatment group for a potential additional IE on the refresher trainings (although this option was later discarded). Results using different values for the R^2 are presented. in Table A - 2 below.

Table A - 2. Power calculations for maize yields

Total # of groups in control/ treatment group	R^2	Size of cluster	Sample size in control/ treatment group	Total sample	MDES	Std. MDES	Per cent change
225	0%	4	900	1800	0.186	0.159	10.35
225	30%	4	900	1800	0.156	0.133	8.66

Source: LORTA team
Note: One cluster is composed of one LF plus three of his or her CFs. Accounting for a 20 per cent attrition does not substantially alter the results.

Appendix 4. ADDITIONAL FIGURES

Figure A - 1. Average elevation in Malawi

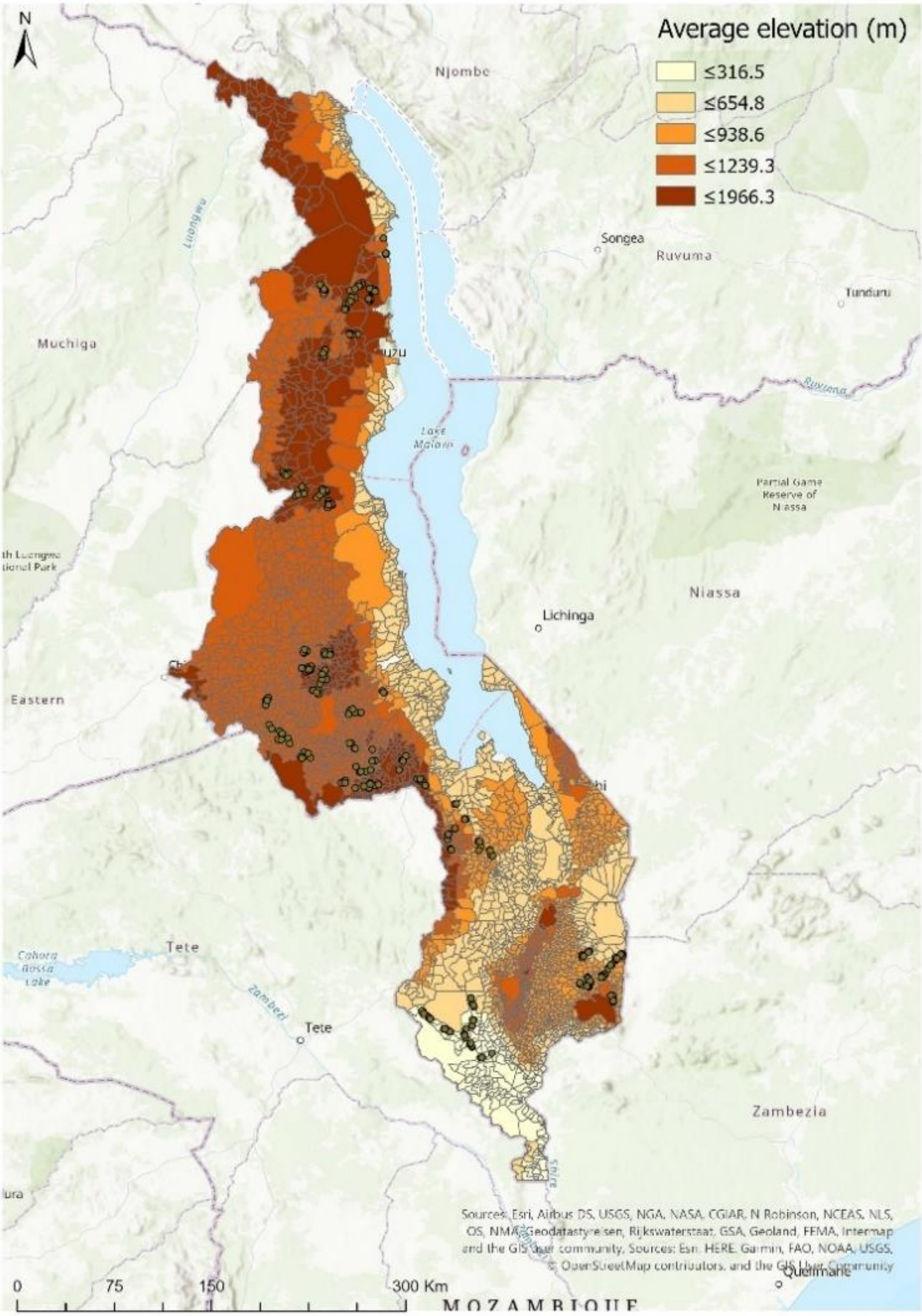


Figure A - 2. Average temperature in Malawi (2012–2018 rainy seasons)

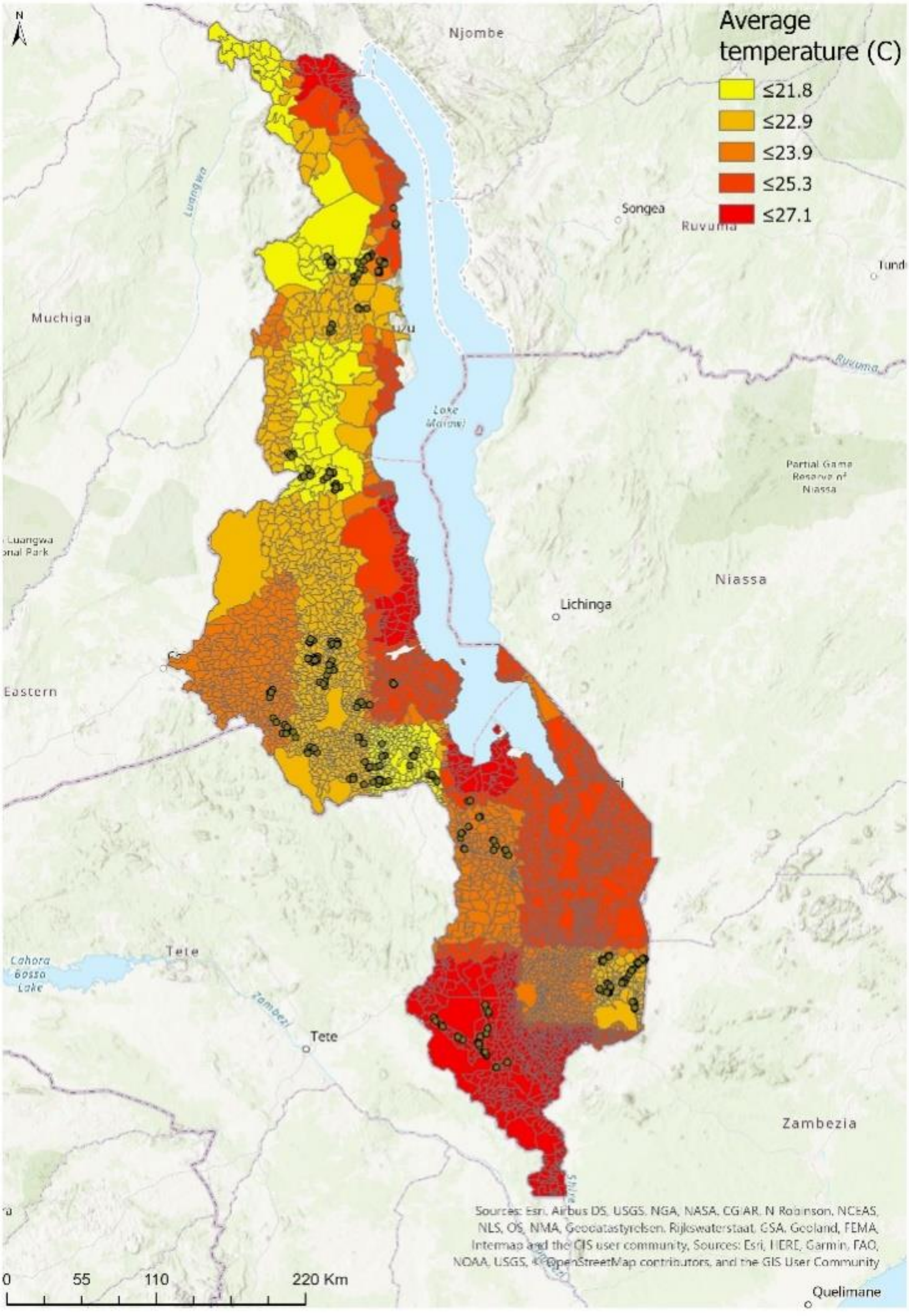


Figure A - 3. Average precipitation in Malawi (2012–2018 rainy season)

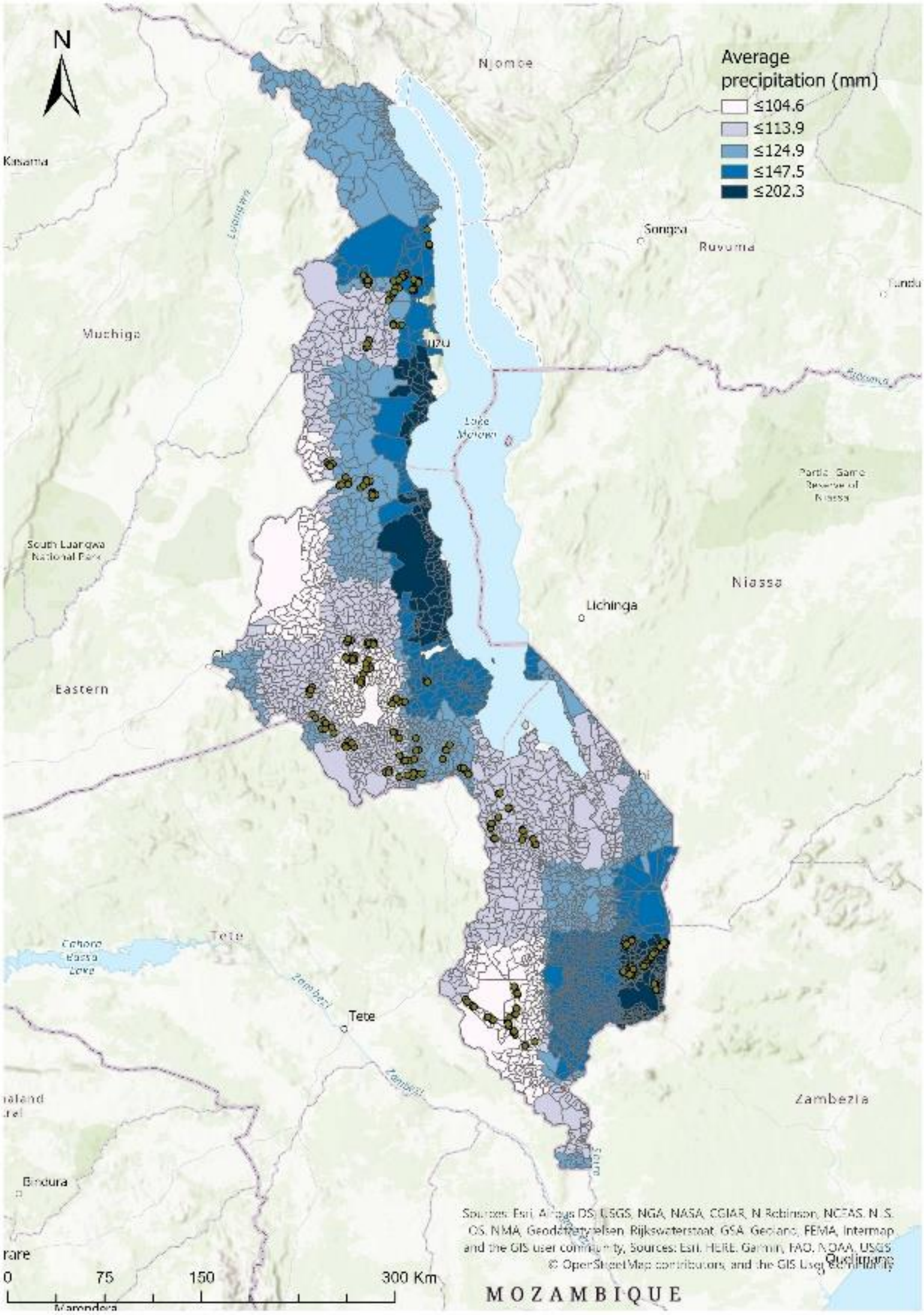


Figure A - 4.   Total precipitation in Malawi (2012–2018 rainy season)

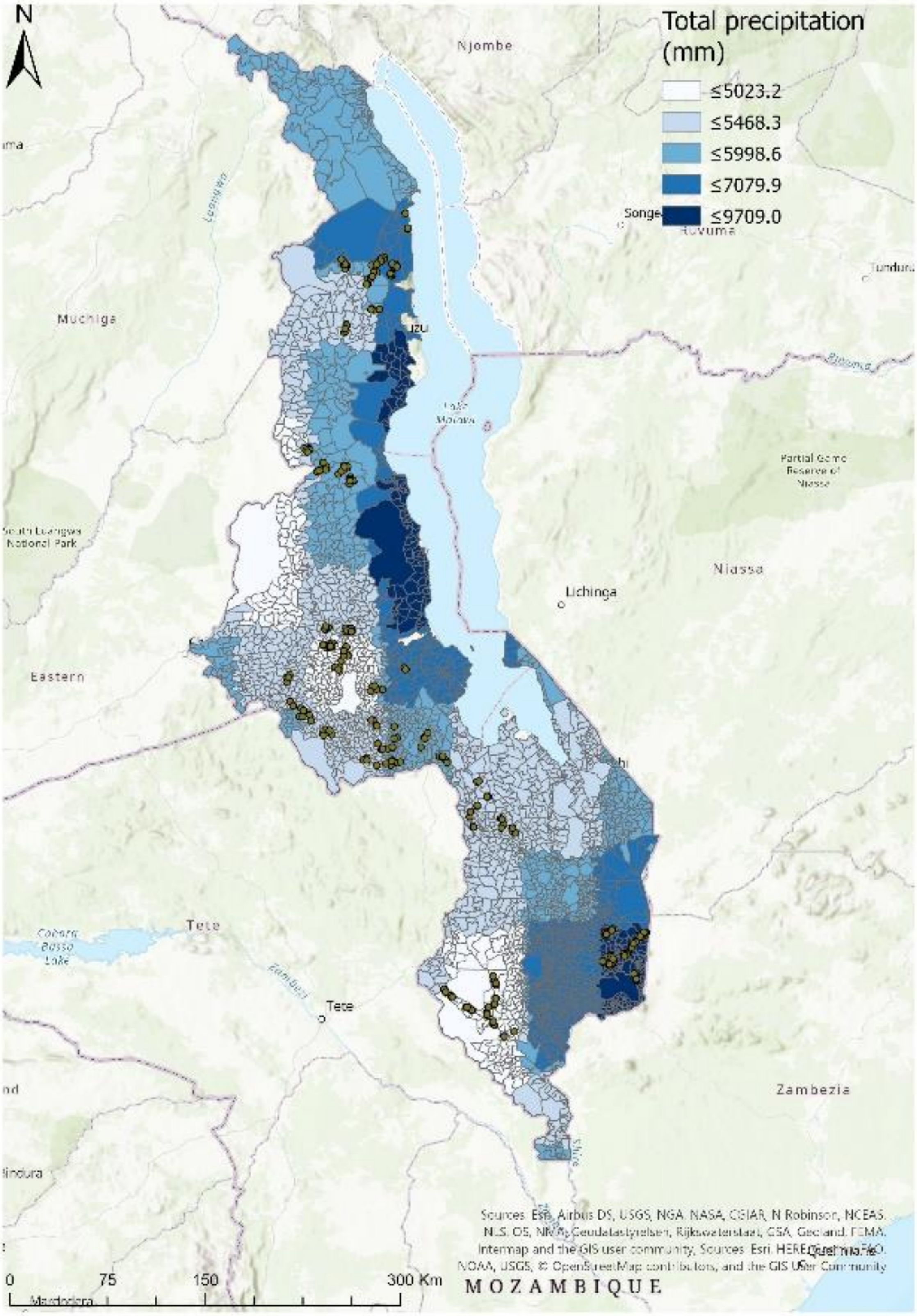


Figure A - 5. Average temperature by season in Malawi (1901–2019)

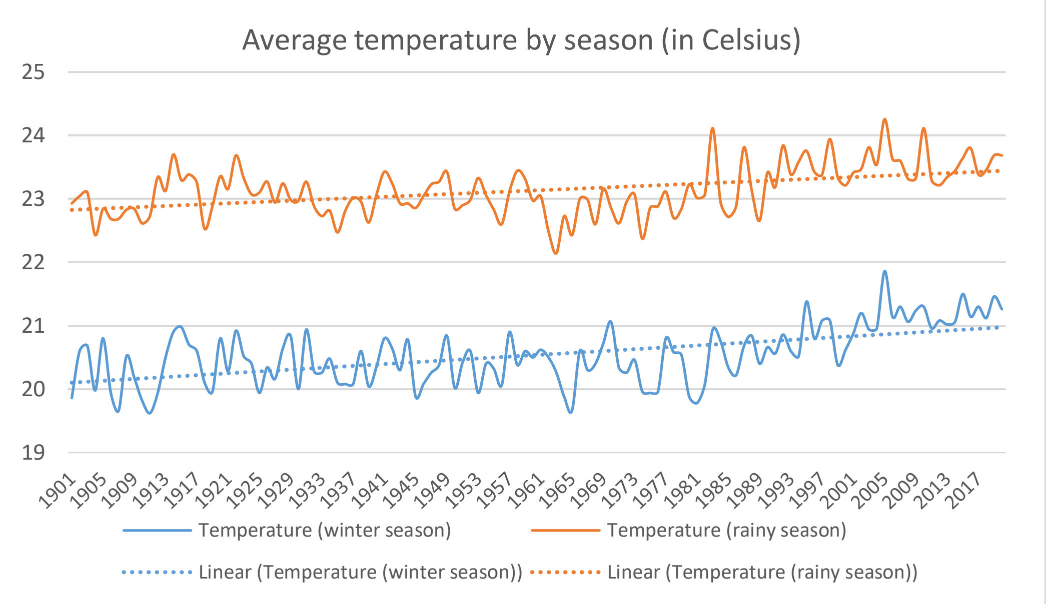
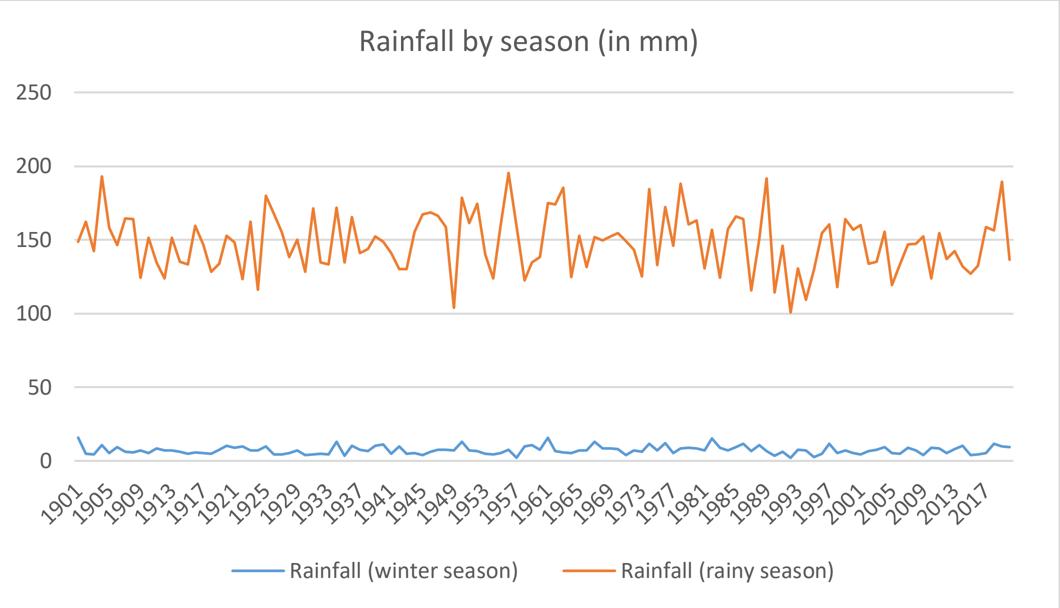


Figure A - 6. Average rainfall by season in Malawi (1901–2019)



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