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Research article

Pathways to adoption and mitigation: A dynamic perspective on good agricultural practices in Rural Malawi☆

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A B S T R A C T

Many researchers have noted the limited adoption of farming management practices that should increase the resilience of smallholder farmers to weather shocks and mitigate their impact on the changing climate in sub-Saharan Africa. In this paper, we evaluate the dynamics of adopting "good agricultural practices" in Malawi, using data from a three-wave panel collected as part of an impact assessment of the Sustainable Agricultural Production Programme, funded by the International Fund for Agricultural Development. In addition to project impacts, we also evaluate additional mechanisms though which farmers may learn about the costs and benefits of different practices. We also evaluate the extent to which climatic conditions – such as being located in drought-prone or heavy rainfall areas – drive adoption decisions. Given the three waves of data, we first look at the range of adoption pathways observed, through the use of an adoption pathway trees. We identify six pathways, noting that adoption is not continuous for a large percentage of households. We then run a multinomial logit to assess the factors that increase the likelihood of falling into different adoption categories vis-a-vis remaining a never adopter. Results suggest that learning through information dissemination, such as through the SAPP project, and wider learning opportunities significantly increased the likelihood of pursuing different adoption pathways, while climatic conditions and learning through observing have limited impacts. On the other hand, for land-intensive management practices, being located in drought-prone areas or being located in areas prone to heavy rainfall increased the likelihood of pursuing different adoption pathways, as did greater ability to learn by observing. Learning by information sharing had limited impacts for land-intensive adoption pathway decisions. Overall, results suggest that information dissemination is important, though the mechanism differs by type of practice promoted. Flexibility in adoption status is an attribute of this system and there is a need to identify and promote practices that are both flexible and increase resilience to climate change.

1. Introduction

The 2021 IPCC report states that "*Increasing weather and climate extreme events have exposed millions of people to acute food insecurity and reduced water security, with the largest impacts observed in many locations and/or communities in Africa, Asia, Central and South America, Small Islands and the Arctic*" (IPCC, 2021). Rural small-scale producers in developing countries are among the most exposed to and most impacted by climatic change and by weather shocks such as floods and droughts. At the same time, the most recent report from the Climate Policy Initiative (CPI, 2022a) indicates that between 2017 and 2020, climate finance to agriculture, forestry, other land uses, and fisheries (AFOLU) dropped. The AFOLU sectors are dramatically underfunded and would require a nearly 26-fold increase in annual funding, i.e., USD 423 billion annually by 2030, to shift to a low-carbon and climate resilient trajectory (CPI, 2022b).

Within this global context, rural households in Malawi are particularly vulnerable to the impacts of climate change and the expenses

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associated with land degradation. A large part of that vulnerability is related to the heavy reliance of rural smallholders on rain-fed agriculture as their primary source of employment (Malawi National Statistical Office, 2020). Average maize yields are low and highly dependent on erratic rainfall. For instance, maize yields following the relatively normal 2012/2013 rainy season were 1804 kg/ha, but fell to just 1117 kg/ha following the 2015/2016 rainy season that was characterized by wide-spread drought (McCarthy et al., 2018). More recently, at the country level, Malawi's maize output dramatically declined from 4.6 million metric tonnes in the 2020/21 farming season to 3.7 million metric tonnes in the 2021/22 season, due to a combination of climate related factors such as drought and tropical cyclones combined with inadequate supply of subsidized fertilizer (MAIWD, 2022).

Livelihood challenges in rural Malawi are further exacerbated by a growing population which is leading to shrinking farm sizes, currently corresponding to just 0.7 ha on average (Malawi National Statistical Office, 2020). Intensive farming and damaging practices are leading to degraded soils with nearly 40% of agricultural land too acidic for decent yields. The Land Degradation Neutrality objective set out by the Global mechanisms of the UNCCD in 2018 estimated that in the case of Malawi, the annual cost of land degradation is USD 320 million, equivalent to 7% of the country's GDP (The Global Mechanism of the UNCCD, 2018).

With the key aim of increasing agricultural productivity given land constraints and climate change challenges, several efforts are being undertaken to help farmers adapt to climate change while improving land management and mitigating their impact. One such effort is the Sustainable Agricultural Production Programme (SAPP). The SAPP is a multi-year program implemented by the Ministry of Agriculture, Irrigation and Water Development (MAIWD), with a budget of USD 51.71 million financed by IFAD, the Government of Malawi and contributions from beneficiaries. The project became effective in October 2012 and has been extended to 2023. The project promoted several "good agricultural practices" (GAPs)[1] to increase productivity and farm incomes, recognizing that different practices would be more suitable and attractive in different settings. The project collected data on beneficiary and control households at baseline, midline and endline, which is the source of data used in this analysis.

Many projects like SAPP have been rolled out in sub-Saharan African countries over the past decades, promoting a range of practices that should reduce vulnerability to weather shocks while mitigating agricultural contribution to climate change (Amadu et al., 2020; Blanco and Lal, 2008; Makate, 2019). However, there is limited evidence of wide-scale adoption across sub-Saharan Africa (Cordingley et al., 2015; Macours, 2019; Shikuku et al., 2017; Takahashi et al., 2020). Various reasons for limited adoption have been put forth, such as: certain practices require knowledge, and sometimes adaptation to local contexts, which increases the riskiness of adoption and dissuades adoption by households with limited risk-coping capacity (Beaman et al., 2021; Sitko et al., 2021); resource constraints such as very small landholdings dissuades adoption of land-intensive practices like bunds, trees and grasses and drainage channels; few working-age adults in the household dissuades adoption of labor intensive practices (Arslan et al., 2014; Asfaw et al., 2016; Adimassu et al., 2014; McCarthy et al., 2018; Ruzzante et al., 2021); limited access to markets to source materials required for certain practices (Makate et al., 2019; Maggio and Sitko, 2019; Kirui and Mirzabaev, 2015; Senyolo et al., 2018) and, the fact that at least some practices need to be adopted continually over a number of years to actually improve outcomes smallholders, tend to be unattractive to poor households with immediate subsistence needs (Jayne et al., 2019; McCarthy et al., 2011; Senyolo et al., 2018).

Given limited widespread adoption of GAPs despite significant resources devoted to spur adoption, in this paper, we focus on evaluating the factors associated not just with adoption, but on patterns of adoption and dis-adoption as well. The theoretical literature largely considers the decision to adopt or disadopt to be a discrete decision (Feder et al., 1985; Khanna, 2001; Moser and Barrett, 2006). However, conditions that can spur adoption and disadoption each growing season can lead to complex patterns of adoption over time. One key factor is weather shocks. If farmers anticipate different types of weather shocks, such as drought or floods, then disadoption in one period may be the best response to that information. As noted in the literature review below, disadoption is generally considered to be a "negative" outcome associated with resource constraints and high costs. However, having the flexibility to adopt and disadopt may itself be valuable (Chen et al., 2022; Mishra et al., 2020. This flexibility may well become more valuable as climate change leads to more frequent and severe weather extremes. At the same time, learning about the benefits to adoption across all possible weather scenarios also becomes more difficult. This paper addresses the research gaps on the factors behind different patterns of adoption and dis-adoption, with a particular emphasis on evaluating the role of different information distribution mechanisms and exposure to weather shocks on those decisions. The analysis of adoption pathways is our main contribution to an otherwise scant literature on patterns of adoption over time (though c.f. Arslan et al., 2014; Chen et al., 2022).

To perform the analysis, we use a three-year panel of observations comparing beneficiaries and a carefully selected control group, which enables us to delve more deeply into the main drivers of adoption as well as into other contextual factors that affect pathways and dynamics of adoption. We identify six adoption pathways followed from baseline to midline to endline. Following insights from the decision-making under risk and innovation diffusion literatures, we develop a conceptual model of the mechanisms that enable farmers to learn about alternative GAPs, the role of climate variables on the adoption pathway choice, as well as the role of other contextual factors such household resource constraints and access to markets.

The paper is structured as follows. In section 2, we briefly describe the project's objectives and activities. Section 3 discusses the conceptual framework and related literature, focusing decision-making under risk and the diffusion and dynamics of adoption. In section 4, we outline our empirical strategy, while section 5 we present the results and discuss the findings. Section 6 concludes.

2. Brief overview of the SAPP project

The goal of the SAPP is to contribute to poverty reduction and improve food security among the rural population of Malawi. The SAPP pursued this goal by addressing key challenges related to three main spheres: 1) knowledge management and technical assistance; 2) low agricultural productivity – due to small landholdings, declining soil fertility and lack of crop diversification; and 3) poorly developed markets for both input and outputs.

Our analysis focuses on project activities that directly addressed the second constraint, low agricultural productivity, through the promotion of GAPs. The GAPs promoted by the SAPP can be ascribed to two main types of practices: relatively labor-intensive and relatively land-intensive. Labor-intensive practices include pit planting, water infiltration pits, organic manure, legume cover crops and compost. Land-intensive practices include grass strips, contour ridges, bench terracing, drainage channels, fertilizers trees, and swales (Cavatassi and Maggio, 2022).

The SAPP was implemented across 46 Extension Planning Areas (EPAs) in six districts in the Northern (Chitipa), Central (Lilongwe and Nkhotakota) and Southern (Blantyre, Chiradzulu and Balaka) regions of Malawi. The selection of the districts was based on four criteria. First, districts were selected according to their agricultural potential with respect to the practices promoted and how these may contribute to increase crop productivity, food security and income of farmers in their territories. Second, the SAPP aimed at targeting districts with relatively

[1] GAPs substantively overlap with other practice groupings such as "sustainable land management" and "climate smart agriculture".

high prevalence of poverty and food insecurity. At the time of the project design, the poverty rate in these districts ranged between 38 and 67 percent, and those defined as ultra-poor varied between 11 and 33 percent. The SAPP-targeted population is represented by smallholder food insecure households who own at least a small piece of land but are unable to produce a surplus to be marketed due to limited resources (e.g. a minimum of 0.2 ha, and a maximum 5 ha, of land). They are often net-buyers of food and represent about 80 percent of smallholders countrywide (Cavatassi and Maggio, 2022; MAIWD, 2016).

The SAPP included a budget for an impact assessment, and three waves of surveys were implemented corresponding to baseline (2014), midline (2018) and endline (2020), described more fully below. SAPP's targeting criteria were fully integrated into the impact assessment, and fully utilized to select control districts and control households.

3. Conceptual framework and related literature

To develop the conceptual framework, we first review the theoretical literature on decision-making under risk in a static framework, and then consider additional factors that affect the dynamics of technology diffusion and adoption pathways.

3.1. Static model of risk-averse decisions under mean-variance approximation to expected utility

To capture factors affecting the adoption decision by risk-averse smallholders, we use the mean-variance approximation to expected utility of income. Though simple, the model captures the impact of expected weather and weather variability on GAPs adoption.

Consider the optimization problem captured in equation (1). Income is equal to the value of output produced minus input costs, $Y = pf(X_i, \mathrm{G}_i; \mathrm{W}, Z) - \sum c_{iX}X_i - \sum c_{iG}G_i$. We posit a composite output function, $Q = f(X_i, \mathrm{G}_i; \mathrm{W}, Z)$, which is multiplied by a composite price index, p. Outputs are a function of traditional inputs chosen, X_i (for example, labor and seeds) as well as any GAPs adopted, G_i, and random weather, W. Outputs are also a function of exogenous household, community and other location characteristics, Z, which affect total factor productivity. The costs to both traditional and GAPs inputs are given by c_{iX}, c_{iG}, respectively. Input costs can be comprised of a number of different cost categories. Input costs include actual cost outlays as well as market-related transactions costs and opportunity costs of owned resources (land, labor). Importantly, GAPs costs can also include transactions costs of learning about GAPs benefits, and costs associated with learning how to implement GAPs under local conditions. We can then write the expected utility maximization equation as follows:

$$EU(Y) = pf(X_i, \mathrm{G}_i; \widehat{\mathrm{W}}, Z) - \sum c_{iX}X_i - \sum c_{iG}G_i - \tfrac{1}{2}[pf(X_i; \widehat{\mathrm{W}}, Z)]\phi_R \sigma_Q^2(\overline{\sigma}_W^2, G_i) \tag{1}$$

The first expression in equation (1) captures expected income, where $\widehat{\mathrm{W}}$ represents expected weather. The last expression in equation (1) captures the costs of risk for risk-averse farmers. ϕ_R is relative risk aversion and σ_Q^2 is the output variance. In turn, output variance is a function of exogenously given weather variance, $\overline{\sigma}_W^2$, as well as GAPs adoption. Adoption of GAPs is posited to reduce the output variability caused by climate variability through absorbing impacts from weather shocks. For simplicity, we can let $\sigma_Q^2(\overline{\sigma}_W^2, G_i) = \overline{\sigma}_W^2 G_i^{-\gamma}$, where γ is a parameter that translates higher GAPs adoption into lower variance. The optimal solutions for inputs are as follows:

$$G_i^* = g(\widehat{\mathrm{W}}, \overline{\sigma}_W^2, \gamma, \phi_R, c_{iX}, c_{iG}, Z) \tag{2}$$

$$X_i^* = h(\widehat{\mathrm{W}}, \overline{\sigma}_W^2, \gamma, \phi_R, c_{iX}, c_{iG}, Z) \tag{3}$$

As captured in equations (2) and (3), maximization leads to optimal input choices that are functions of expected weather, weather variability, the productivity of GAPs in reducing output variability, relative risk aversion, input costs and other relevant exogenous characteristics. With respect to GAPs, the impact of better expected weather conditions is ambiguous and depends on whether the marginal productivity of GAPs usage is increasing or decreasing in expected weather, since the marginal benefits to greater expected income will be offset by lower marginal benefits to reducing risk. Greater climate variability and greater risk aversion will likely increase GAPs usage.[2] The greater marginal effectiveness of GAPs in reducing output variability will increase GAPs usage, while higher GAPs costs reduce usage. Finally, household and community characteristics that increase total factor productivity will increase GAPs usage.

3.2. Dynamics of adoption

The above model captures the incentives to adopt GAPs where farmers are risk averse and where those practices reduce crop production variability. However, it does not explicitly evaluate the costs associated with the adoption decision outside of costs captured in c_{iG}. Additionally, the model assumes that farmers know the benefits to GAP adoption both on average yields and on yield variability. Yet, we know that there are additional costs associated with adoption, primarily related to forming expectations about the benefits to adoption and costs associated with greater uncertainty about these benefits. The first observation, then, is that more risk-averse farmers may not be more likely to adopt GAPs when they are uncertain about the impact of GAPs on expected yields and on yield variability, even if they would be more likely to adopt than wealthier farmers if they were certain about GAP benefits. Much of the literature on technology adoption details the types of mechanisms that may enable farmers to acquire the knowledge they need to increase certainty about average yield and yield variability benefits. A number of researchers point to landholding size as an important factor, since farmers with more land can "afford" to experiment with different practices on a smaller portion of their land to learn about the costs and benefits to different practices (Byerlee and de Polanco, 1986; de Janvry et al., 2017; Foster and Rosenzweig, 1995; Lahiri et al., 2018). For more complex practices, more experienced and more educated farmers are hypothesized to adopt earlier, as they more quickly understand how to apply the practice to achieve optimal benefits (Khanna, 2001). However, despite the theoretical arguments linking land size and education to GAPs adoption, a recent meta-analysis of 204 empirical papers shows that the impacts of these two factors on natural resource management adoption are insignificant (Ruzzante et al., 2021).

Early models of technology diffusion posit that farmers can also learn about costs and benefits by observing the results obtained by early adopters, "learning by observing" (Griliches, 1957; Feder et al., 1985). More recent research also finds that "learning by observing" or "learning by sharing" information through farmer-to-farmer interactions can be important mechanisms for knowledge dissemination (Beaman and Dillon, 2018; Conley and Udry, 2010; Krishnan and Patnam, 2014; Maertens et al., 2021; Nie and Ragasa, 2018; Yamano et al., 2018). Information about benefits and costs can also be disseminated by extension agents, radio and other media, and input vendors, though access to these sources is often relatively low, especially to extension agents (Beaman et al., 2018; Niu and Ragasa, 2018). Heterogeneity in agro-ecological characteristics also makes it difficult to learn by

[2] It is theoretically possible that households facing very high risks will reduce the use of all inputs vis-à-vis those facing more moderate risks. In other words, GAPs adoption can theoretically exhibit an inverse-U shaped relationship with weather variability and risk aversion, where GAPs adoption increases with climate risk up to a certain point, after which it declines. We tested this hypothesis, but did not find significant results on the squared terms, and so do not report those results here.

observing from other farmers' experiences (Munshi, 2004; Takahashi et al., 2020).[3]

In dynamic models of adoption, it is assumed that once a decision has been made, then farmers will continue to adopt thereafter, so-called "threshold" models (Khanna et al., 2000; Seo et al., 2008). Threshold models capture the transition from non-adoption to adoption, but they generally do not consider the conditions under which households may switch back and forth between adoption statuses. Yet, at least some observers have noted that farmers both adopt and dis-adopt technologies. Arslan et al. (2017) document patterns of adoption and dis-adoption of GAPs in Zambia, although the dataset used covered only two time periods. Grabowski et al. (2016) document patterns of adoption and dis-adoption of minimum tillage, also in Zambia. However, neither of these studies evaluate factors affecting the adoption/dis-adoption pathway per se. Chen et al. (2022) develop a dynamic simulation model that captures different patterns of adoption that arise when input and output prices change and where there are costs to switching to adopting or to dis-adopting, where returns to adopting are uncertain, and where farmers are risk-averse. These features of the model result in different patterns of adoption over time including "transient" adoption, where farmers switch between adoption and dis-adoption as output, input and transactions costs fluctuate.

The GAPs promoted by SAPP are likely to exhibit different costs to adopt or dis-adopt. For instance, it is more costly to invest in soil and water conservation structures than to apply organic manure or mulch, and dis-adoption will be more costly as well. As developed more fully below, we hypothesize that GAPs that are land-intensive – fertilizer trees, grass strips, terraces, drainage channels – will in general be more costly to adopt and dis-adopt than labor-intensive practices. This distinction will enable us to test whether patterns of adoption are consistent with hypotheses from the research on the dynamics of adoption presented above.

To summarize hypotheses from the dynamics of adoption literature, continuous adoption is more likely where farmers feel more confident in their knowledge of the distribution of benefits from adoption, are less risk-averse to experimenting, and have larger landholdings on which to experiment. The ability to acquire knowledge by learning through observation of potential benefits will depend on the experience of other farmers in one's network, and the extent to which land quality is relatively similar across plots managed by other farmers in one's network. The ability to learn through information dissemination will be greater when access to external sources such as extension agents, and other sources of agricultural information is greater. Transient adoption is more likely when GAP adoption is essentially a yearly decision (with no or low fixed costs) and adoption costs and output prices are relatively volatile, and where costs of switching between adoption and dis-adoption is relatively low. Dis-adoption is more likely to occur when farmers initially adopt but do not realize expected benefits, when adoption costs trend higher, and where opportunity costs of taking land out of production increase (e.g. increase in number of household members).

4. Empirical strategy

4.1. Data

SAPP districts were chosen based on their potential for sustainable agriculture and high incidence of poverty and food insecurity (IFAD, 2011). To select control districts, Chirwa et al. (2015) used information on "livelihood zones", which are defined as "areas where households share similar options for obtaining food or income" (MVAC, 2005) to match control districts with treated districts that share the same or similar livelihood characteristics. Results from the Malawi Third Integrated Household Survey also indicate that the control districts were a decent match to the SAPP districts; for instance, poverty rates in SAPP districts ranged from 33% to 68%, while poverty in control districts ranged from 37% to 57% (Malawi National Statistical Office, 2020).

Households that were interviewed at baseline were tracked for the construction of the midline and endline datasets. The tracking protocol focused on a few key principles:

- No more than one household was tracked at midline for each baseline household, and no more than one household was tracked at endline for each midline household.
- No replacement was done for households that could not be interviewed.
- Minimum requirements to be interviewed were:
  - o At least one member aged 12+ at baseline be present at midline.
  - o Closest geographical location to baseline location, but still located within the set of SAPP districts. So, if all members of a specific household had moved to a non-SAPP district, then no interview took place for that household.

Of the 1800 baseline households, 1656 were located at midline, giving an 8% rate of attrition. Of those 1,656, 1535 were located at endline, giving a 3% rate of attrition. Overall, the attrition rate observed between the three waves is in line with other panel data collected in Malawi (c.f. Malawi National Statistical Office, 2020). Of the losses due to attrition, about half were due to households relocating outside the study area, while the other half simply could not be found and likely also relocated outside the study area. There were also 14 households that moved from treated to control districts or vice versa. Removing these households leads to a sample size of 1524. We also note that there was no statistical difference in rates of attrition between the treated and control households.

4.2. Endogenous variables and empirical strategy

The dataset contains data on a relatively large number of GAPs,28.[4] Estimating the adoption pathways for all GAPs is simply not feasible. Instead, we aggregate across different practices. There are a number of ways the data can be aggregated, following different rationales. We have chosen to aggregate practices depending on whether they are relatively land or relatively labor intensive. The rationale behind this aggregation strategy is that the ability to adopt land- and labor-intensive practices is affected by different household constraints. In our dataset, only about a third of households hired any labor, and overall the proportion of hired to total labor days is just above 10%. Additionally, most households must augment farm income with off-farm income in order to meet basic needs. Thus, labor constraints can be binding. With respect to land constraints, we note that though 18% of households rented land in, the overall proportion of land rented in to total cultivated was just 7%. Furthermore, incentives to invest in GAPs on rented-in land are significantly lower than for own land, since many GAPs will provide benefits for more than one season. The average landholding size is just over 1 ha. Thus, own land constraints can also be binding. Finally, conceptually, we expect different patterns of adoption for practices that are relatively less costly to adopt and dis-adopt versus those that are more costly. Given the characteristics of the practices, we hypothesize that labor-intensive practices tend to be less costly to adopt and dis-adopt than land-intensive practices.

An alternative aggregation method would be to distinguish between

[3] Another key aspect posited to affect adoption is the "divisibility" of the practice (Zilberman et al., 2014). For lumpy investments, such as much irrigation equipment, purchase by smallholders will be limited. While important in certain contexts, the GAPs promoted under the SAPP project are largely divisible.

[4] Descriptive statistics for the full list of GAPs are provided in Appendix 1.

different outcomes, for instance, whether the primary benefit of a GAP is to increase soil fertility versus reduce soil erosion and manage water. In practice, many of the labor-intensive practices primarily have soil fertility benefits, while many of the land-intensive practices primarily have soil and water conservation benefits. As a robustness check, we run the analyses on practices aggregated based on this outcome distinction.

The labor-intensive practices we include are whether the household adopted pit planting, infiltration pits, legume cover crops, or applied organic manure or compost. Adoption rates for these GAPs ranged from 2% to 28% at baseline. For land-intensive practices, we include adopting grass strips, contour ridges, bench terraces, drainage channels, swales, fallow, and fertilizer trees. Adoption rates for these GAPs ranged from 2% to 18% at baseline. There are a number of other GAPs that we do not include in these categories, primarily those for which adoption was relatively high at baseline and with which many farmers were already familiar before the start of the project. These include intercropping with any crops, having any legume crops, and box ridges, where adoption rates at baseline ranged from 44% to 80%. Including these variables in the aggregated variable means they would dominate the aggregation measure. Since the goal of SAPP was to increase adoption of practices primarily through knowledge building, it makes sense to focus on those practices for which knowledge was limited at baseline.

We take a two-pronged approach to evaluating the dynamics of adoption. We first start with a descriptive analysis by evaluating adoption trees. The trees trace out the path of adoption and dis-adoption, capturing the proportion of households along each path at midline and then at endline. Second, we estimate a multinomial logit that captures different adoption/dis-adoption patterns suggested by the adoption tree analysis. The use of a multinomial logit model is justified by the fact that it is particularly suited for situations where the dependent variable has more than two categories. In our case, while one category, i.e. never adopters, can be considered the worst outcome scenario, there is no inherent ranking between the remaining categories. Unlike binary probit models, which are limited to two outcome categories (e.g., adopter vs. non-adopter) and do not allow us to fully utilize the set of observations for each estimate, the multinomial logit model allows us to evaluate multiple adoption pathways simultaneously. This approach leverages the entire set of observations and allow us to conduct a more nuanced analysis of the factors driving farmers' decisions.

We create six adoption path categories for each GAP category as described in Table 1 below:

We can write the equation for the optimal pathway for household i as follows:

$$P_{ik}^{*} = \alpha + \partial_1 SAPP_i + \beta_{\widehat{W}} \widehat{W}_i + \beta_{\overline{\sigma}_W^2} \overline{\sigma}_{W_i}^2 + \beta_T TCA + \beta_{CD} CD_i + \beta_Z Z_i^{HH,C,Adm} + e_i \tag{6}$$

P_{ik}^{*} is the pathway taken by household i for GAP category k. P_{ik}^{*} takes a value from 1 to 6, representing each of the potential adoption/dis-adoption pathways; $SAPP$ is the treatment dummy; $\widehat{W}$ includes the historic average of weather variables, $\overline{\sigma}_W^2$ captures a measure of variance of weather variables; and, TCA is a vector of transactions costs associated with adoption and dis-adoption decisions. As discussed more fully below, we do not have direct measures of risk aversion. Instead, we will use a consumer durables index, CD_i, to proxy for risk-aversion, recognizing that it also reflects cash and credit constraints. Variables in $Z^{HH,C,Adm}$ include all relevant household, community and administrative-level variables hypothesized to affect farm productivity and transactions costs and that were not influenced by SAPP. For household variables, we use baseline variables to ensure that their levels are not affected by treatment. We discuss specific exogenous variables used more fully below in section 4.3.

Since the project did not follow a random control design, we use propensity score matching to generate inverse probability weights to address any issues of selection bias (Gertler et al., 2016). In our case, we have good information on the project's targeting criteria at both geographic and household levels that strengthens the rationale for using inverse probability weights. We also have a rich set of data that allows us to include relevant variables identified in the literature to affect the adoption decision. Finally, to ensure that the error term, e_i, is distributed $N(0, \sigma_e^2)$, all estimations' error terms are clustered at the primary sampling unit level (the enumeration area in this case).

Table 1
Adoption path category Descriptions.

Category	Description
Never Adopter	Households that do not adopt any practices in the relevant GAP category in any of the three waves
Dis-adopter	Households that had adopted at baseline, but dis-adopted at either midline and endline, or just at endline
Experimenter	Households that had not adopted at baseline, adopted at midline, and dis-adopted again at endline
Adopter	Households that had not adopted at baseline, but did adopt either at midline and endline, or just at endline
Flexible Adopter	Households that had adopted at baseline, dis-adopted at midline, and adopted again at endline
Always Adopter	Households that adopted the relevant GAP category in all three waves

4.3. Exogenous variables – GAPs adoption

4.3.1. Climate and agro-ecological variables

For the climate variables, we use rainfall covering flowering season. For maize, the critical flowering stage typically occurs in the 5th-8th dekad after the onset of the rainy season (Evans and Cassel, 1996). Previous work has also established that flowering period measures of rainfall have greater predictive power than total season measures in regressions of maize yields and total value of production in Malawi (McCarthy et al., 2021). Rainfall data is from the African Rainfall Climatology 2 (ARC2) dataset produced by the National Oceanic and Atmospheric Administration (NOAA). Temperature spikes can have significant negative impacts on crop yields across the full season (Schlenker and Roberts, 2009; Steward et al., 2018). Because the impacts of temperature on yields is hypothesized to have a discreet threshold effect, we evaluated a number of thresholds established in the agronomic literature to affect maize production, and selected the threshold of 35 °C at noontime, as this is the point at maize growth start to decline according to the literature (see for instance Sinsawat et al., 2004; Waqas et al., 2021). Historical data on maximum daily temperatures are obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA INTERIM reanalysis model dataset.

Because there is limited guidance on what specific climatic variables to use in the analysis, we explored the predictive power of a number of specifications on the probability of adopting GAPs at baseline. After a systematic evaluation of performance in terms of explanatory power and robustness, we have selected two measures to capture expected weather and climate variability. The first is an index that captures hot, dry and high drought risk conditions. We ran a principal components factor analysis on mean flowering period rainfall, the coefficient of variation of flowering season rainfall for realizations that were below mean rainfall, and the mean number of times noon-time temperatures exceeded 35 °C over the full season. The factor scores are positive on the coefficient of variation and temperature spikes, and negative on mean rainfall. We thus interpret this index to capture drought proneness, and hereafter refer to it as the Drought Prone index. We separately control for the likelihood of receiving excessive rainfall and flooding by constructing the proportion of years for which rainfall exceeded one standard deviation above the mean, and we refer to this variable as Heavy Rainfall Prone. The two climate variables capture different climatic conditions, and they are not significantly correlated (pairwise correlation of −0.004). Finally, we note that the NOAA dataset contains observations going back to 1983. We evaluated the performance of using different time spans on which to construct our climate variables, and determined that using the 10 years previous to baseline (2004–2013) performed slightly better than using the full series, though both perform similarly.

To control for agro-ecological conditions, we have matched household data with data from FAO's soil limitation maps, derived from the Global Agro-Ecological Zoning (GAEZ) program, which is a global scale raster dataset providing an assessment of combined soil qualities, in order to assess crop-specific edaphic suitability, with a 5 arc-minute resolution, or about 9×9km at the equator. From this data, we have created a dummy variable that takes a value of 1 if the household location is considered to suffer from soil and/or terrain limitations. In our sample, soil limitations affect 57% of households. The impact on adoption of GAPs is ambiguous. If the marginal benefits to adoption – in terms of higher and more stable yields – are relatively large under soil limitations, then this favors adoption vis-à-vis those with no soil limitation. We also include the altitude at the household's location, as well as dummy variables to capture slope. The dummy variables take a value of 1 if the average slope in the household's locale is categorized as flat or slightly sloped. Both altitude and slope are from SRTM30 dataset, provided by the U.S. Geological Survey. Steeper land should increase adoption of GAPs, particularly those that reduce soil and water erosion; however, soil quality tends to vary more in areas with greater slopes at higher elevation, which may limit learning by observing (Li et al., 2017a,b).

4.3.2. Transaction cost of adopting GAPS

Households with larger areas of land have greater capacity to experiment with different GAPs without threatening household subsistence requirements and hence lower costs of learning by doing, while larger households face lower opportunity costs of adopting new practices, particularly land-intensive practices. At the household level, we also include the highest level of education attained by any adult in the household at baseline. Higher levels of education should reduce transactions costs of learning about the benefits and costs of new farming practices, though it may also be associated with greater off-farm income opportunities so that the hypothesized impact is ambiguous. We include a measure of agricultural assets, calculated using a principal components factor of agricultural implements.[5] Greater agriculture-specific assets increase labor productivity and may lower costs GAPs adoption for some practice, and they may also lower costs of transient adoption.

We proxy accessibility to commercial input markets using the distance to the nearest weekly market; better access should lower than costs of purchased inputs, increase access to information disseminated in the markets, and reduce costs of transient adoption by assuring more reliable access to inputs over time. To gauge access to information dissemination we include whether the household is located in SAPP community (treated), and we also use administrative data from the Ministry of Agriculture on the number of farm families within each extension planning area (EPA) (a sub-district administrative level), which we have matched to our household data.[6] Our assumption is that extension agents will reach more households in more densely populated EPAs where more families are located, reducing the transactions costs of obtaining information from extensionists. Finally, the community-level survey included questions on the share of households who had adopted any land-intensive GAP or any labor-intensive GAPS at baseline in any given community. Greater shares should lower costs of learning about GAP benefits. Conceptually, we expect that, starting from a low share, a higher adoption rate in any given community will have relatively large impacts on the ability to learn by observation, but that marginal impacts taper off as the share increases further. To capture these, we include dummies of the second and third terciles of adoption shares, with the lowest tercile being the omitted category.

4.3.3. Wealth and demographics

To proxy wealth levels, we use an index calculated using a principal components factor analysis of household durables and housing characteristics.[7] The hypothesized impact of the wealth index is ambiguous. We presume that wealthier households are less risk-averse, so that any marginal benefits to risk reduction from the adoption of GAPs will be lower vis-à-vis more poor households. However, wealthier households are less likely to be resource constrained, and thus more likely to adopt GAP practices, particularly GAP practices that increase average land and labor productivity. And, if benefits are not known, wealthier households are more likely to engage in risky experimentation. Finally, we include a dummy for whether or not the household head is female, to capture lower access to resources such as credit and access to extension services.

5. Results and discussion

5.1. GAPs adoption tree

5.1.1. We identify six adoption pathways for both labor-intensive and land-intensive practices, showing that adoption is dynamic rather than linear and that a significant portion of households engage in transient adoption, with many adopting and then dis-adopting

Fig. 1a and b below present the adoption/dis-adoption trees for land- and labor-intensive GAPs, respectively. At the top of the tree, we have the number of households adopting and non-adopting at baseline. In the middle of the tree, we have the percent of households adopting and dis-adopting at midline, for each baseline adoption status. Finally, the bottom of the tree gives the percent of households falling into our six categories: Always Adopters, Dis-Adopters, Flexible Adopters, Adopters, Experimenters and Never Adopters. Here we focus our discussion on whether the adoption trees support our hypotheses on adoption pathways.[8]

5.1.2. Labor-intensive practices show higher rates of transient adoption and dis-adoption among non-adopters, while land-intensive practices are more likely to have flexible adoption among initial adopters

First, we hypothesize that transient adoption (flexible adoption, experimenter) and dis-adoption are more likely to occur for labor-intensive practices versus land-intensive practices. There is support for this hypothesis for those who start out as non-adopters, with 32% of

[5] The productive asset index is built using the first factor of a principal component analysis on a set of count variables capturing the number of oxcart, ploughs, hoes, sickles, axes, bush-knifes, and wheelbarrow owned by the households.

[6] We do have household level information on whether a lead farmer or agricultural extension officer resides in the community but did not ultimately include these variables in the estimations. First, it appears that respondents may have considered lead farmers to be agricultural extension officers, and responses also varied within the same community. Secondly, the effectiveness of lead farmers has been shown to be quite limited (c.f. Beaman et al., 2021). In our case, these variables were not significant in explaining GAPs adoption, and given potential measurement errors were dropped from the estimations.

[7] The durable asset index is constructed using the first factor of a principal component analysis on a set of indicators capturing whether the household owns any radio, radiocassette, tv, refrigerators, bicycles, motorcycles, car trucks, cell phone, bed, tables, mattress, solar panel, water can, treadle pump, and sewing machine.

[8] This is the first time in the literature that adoption pathways have been clearly discerned over a period of almost a decade. Understanding these pathways over a stable sample is often constrained by attrition (i.e., households dropping out of the sample), as well as other factors that may impede follow-up, such as migration, lack of updated contact information, or households splitting or merging over time (see Falaris, 2003; Young et al., 2006; for discussions on attrition in longitudinal surveys).

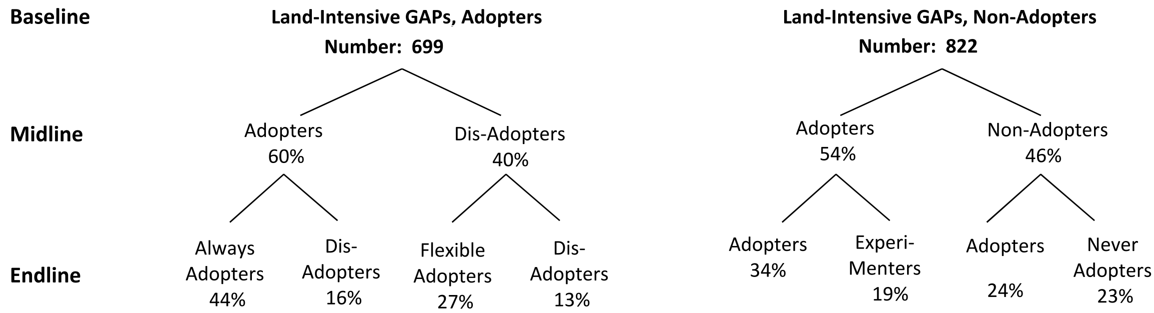

Fig. 1a. Dynamic of adoption of Land-Intensive GAP from Baseline to Endline.

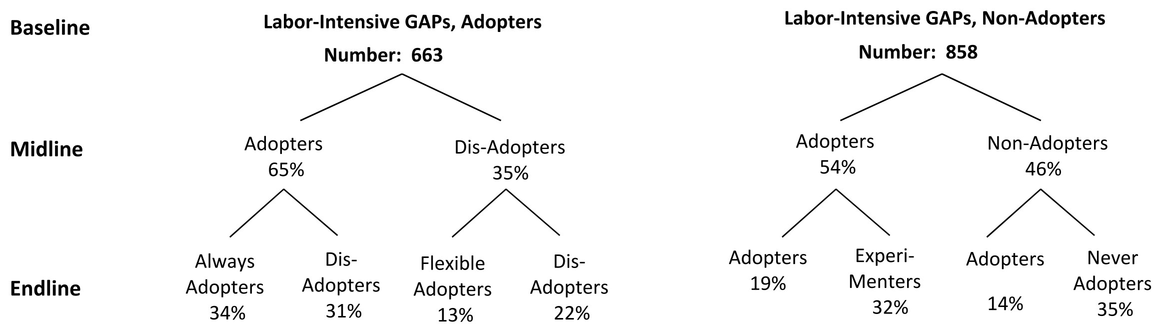

Fig. 1b. Dynamic of adoption of Labor-Intensive GAP from Baseline to Endline.

households following experimenter path for labor-intensive practices versus 19% for land-intensive practices. On the other hand, for those who start out as adopters, the pattern is reversed with 27% of households following a flexible adoption path for land-intensive practices versus 13% for labor-intensive practices. With labor-intensive practices, adopters who dis-adopted at midline instead were more likely to continue as dis-adopters. Those who begin as adopters likely have more knowledge than non-adopters at baseline, and thus it may be that flexible adoption is responding to current period price fluctuations versus costs of learning and adapting, following Chen et al. (2021). This also implies that transition costs for both types of practices are not relatively very high.

5.1.3. *Labor constraints are more binding than land constraints*

Second, the evidence also suggests that the labor constraint may be more binding than the land constraint. A relatively greater share of households are adopters of land-intensive GAPs at baseline and endline vis-à-vis labor-intensive GAPs, and there are fewer never adopters of land-intensive GAPs. Further, dis-adoption rates are much higher, and adoption rates much lower, for labor-intensive versus land-intensive GAPs.

5.1.4. *The delayed benefits of land-intensive GAPs likely contribute to lower dis-adoption rates*

Third, it may take more time for the benefits of land-intensive GAPs to materialize, making it more difficult for the household to determine whether they should continue adopting such practices. This too should lead to less rapid dis-adoption for land-intensive GAPs as seen in the lower dis-adoption rates at endline.

At first glance, it may seem somewhat contradictory that the labor constraint may be more binding than the land constraint in the Malawi context, given that most households have small cropland holdings but are not unduly small in terms of household members. It is likely related to the fact that many households in Malawi must augment their crop incomes with off-farm income sources leading to relatively high opportunity costs of labor. Other research has documented substantial demand for labor-saving technologies by smallholders, even where land sizes are relatively small (Ricker-Gilbert et al., 2014; Sitko et al., 2021; Gono and Takane, 2018).

5.2. *Propensity score matching*

Table 2 reports the summary statistics of the explanatory variables, before and after the propensity score matching (PSM). As the summaries displayed in Table 2 suggest, treated households differed from control households on a number of characteristics, particularly on the drought-

Table 2
Summaries of matching variables before and after matching.

Variables	Before Matching			After Matching		
	Treated	Control	*t*-test	Treated	Control	*t*-test
Own Land, Rainy Season	0.957	1.204	−2.81	0.957	0.888	1.09
HH Size	4.911	5.093	−1.44	4.911	4.965	−0.47
Ag. Assets	0.069	0.080	−3.57	0.069	0.071	−0.73
Consumer Durables Index	0.124	0.154	−3.86	0.124	0.124	−0.06
Dummy, Female Head	0.299	0.262	1.42	0.299	0.284	0.61
Max. Years Education	7.593	8.006	−2.25	7.593	7.202	2.27
Drought-Prone	0.129	−0.270	8.84	0.129	0.068	1.39
Heavy Rainfall-Prone	0.186	0.160	10.05	0.186	0.191	−2.32
Soil Limitation	0.498	0.687	−6.75	0.498	0.522	−0.88
Dummy, Slope Flat or Slight	0.678	0.463	7.70	0.678	0.687	−0.35
Distance, Weekly Market	5.820	7.006	−3.33	5.820	4.907	3.07
# Farm Families (10K)	2.314	1.720	9.51	2.314	2.232	1.25
% Comm. Adopt Labor GAPS	0.296	0.287	1.09	0.296	0.292	0.46
% Comm. Adopt Land GAPS	0.302	0.258	4.63	0.302	0.313	−1.15
Altitude (ln)	6.811	6.822	−0.55	6.811	6.709	5.48

prone index, heavy rainfall-prone, soil limitations and the number of farm families within the extension planning area. In particular, treated households were more exposed to extreme weather events, more likely to have soil limitations but also more likely to have more farm families within their extension planning area. Treated households were also more likely to have fewer assets. After matching, differences are generally not significant, and bias is significantly lower for all but altitude. Overall, mean bias declines from 26.1 before matching to 7.4 after matching, while median bias declines from 20.3 to 5.0.

5.3. *GAPS multinomial logit results*

Tables 3 and 4 present the results from the weighted multinomial logit estimations with clustered standard errors for select variables. In particular, we do not report results for whether the household head is female, maximum education in the household and the consumer durables index, as these are generally not significant; full results are reported in Appendix 2. The dependent variables are the categories of adoption of labor- and land-intensive practices, respectively. In both cases, the omitted category is never adopters, so the coefficients are interpreted with respect to the never adopters.[9]

Table 3
Determinants of Labor-intensive adoption pathways (marginal effects of selected indicators).

Variables	Adopters	Flexible Adopters	Experi-menters	Dis-adopters	Always Adopters
Treated	1.050[c]	0.577	−0.235	0.328	0.705[a]
	(0.25)	(0.37)	(0.31)	(0.25)	(0.38)
Agro-Climate					
Drought-Prone	−0.181	−0.151	0.02	−0.042	0.143
	(0.15)	(0.26)	(0.21)	(0.16)	(0.25)
Heavy Rainfall-Prone	−0.509[a]	0.466	−0.357	−0.024	0.046
	(0.28)	(0.40)	(0.30)	(0.33)	(0.34)
Soil Limitations	−0.386	−0.143	−0.484	0.005	−0.27
	(0.33)	(0.43)	(0.31)	(0.25)	(0.46)
Slope, flat or slight	0.231	0.426	0.279	0.229	0.198
	(0.25)	(0.40)	(0.30)	(0.26)	(0.41)
Altitude	0.966[b]	2.167[c]	0.974[b]	1.227[c]	0.998[a]
	(0.38)	(0.75)	(0.44)	(0.39)	(0.53)
Innovation Costs					
Own Land, Rainy Season	0.209[a]	0.079	0.167	0.084	0.12
	(0.12)	(0.15)	(0.14)	(0.12)	(0.14)
HH Size	−0.019	−0.058	−0.124[a]	−0.032	−0.052
	(0.05)	(0.08)	(0.07)	(0.05)	(0.07)
Ag. Assets	0.671[b]	0.578	0.551[a]	0.674[a]	1.141[c]
	(0.28)	(0.38)	(0.31)	(0.41)	(0.37)
Distance, Weekly Market	0.002	0.034	0.016	0.030[b]	0.036
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)
# Farm Families	0.232[a]	0.561[c]	0.402[c]	0.536[c]	0.717[c]
	(0.13)	(0.20)	(0.15)	(0.11)	(0.17)
% Comm. Adopt, Mod.	0.265	0.79	0.657[a]	0.27	0.939[b]
	(0.33)	(0.48)	(0.34)	(0.33)	(0.45)
% Comm. Adopt, High	0.223	0.895[a]	0.441	0.117	0.935[b]
	(0.31)	(0.51)	(0.35)	(0.29)	(0.39)
Constant	−7.772[c]	−19.738[c]	−7.163[b]	−10.583[c]	−10.857[c]
	(2.71)	(5.73)	(3.15)	(2.80)	(3.77)
Log-Likelihood	−3857.11				
Pearson's Chi Square			61.71		
p-value	0.015				
Observations	1205				

Notes: the table displays the result from the coefficients of a weighted multinomial logit on the five adoption pathway categories of labor-intensive practices at household level, where Never Adopt is the baseline category. The pathways are defined by the adoption status of the respondent household captured in the three waves under study (2014, 2018, 2020). Full table of results are found in Table A1 in Appendix 1. Significance: Standard errors, in parentheses, are clustered at community level.
[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.

Table 4
Determinants of Land-intensive adoption pathways (marginal effects of selected indicators).

Variables	Adopters	Flexible Adopters	Experi-menters	Dis-adopters	Always Adopters
Treated	0.112	0.34	0.13	0.001	0.358
	(0.278)	−0.393	−0.267	−0.256	−0.35
Agro-Climate					
Drought-Prone	0.402[b]	0.585[c]	0.022	0.025	0.604[c]
	(0.177)	(0.191)	(0.171)	(0.181)	(0.184)
Heavy Rainfall-Prone	0.754[c]	0.085	0.087	−0.016	0.314
	(0.289)	(0.408)	(0.295)	(0.283)	(0.366)
Soil Limitations	0.148	0.264	0.460[a]	0.336	0.109
	(0.300)	(0.302)	(0.270)	(0.284)	(0.328)
Slope, flat or slight	0.057	−0.731[a]	0.19	−0.267	−0.482
	(0.295)	(0.389)	(0.294)	(0.296)	(0.346)
Altitude	0.784[b]	1.351[c]	0.126	0.192	0.973[b]
	(0.352)	(0.412)	(0.296)	(0.348)	(0.408)
Innovation Costs					
Own Land, Rainy Season	−0.022	−0.071	−0.212	0.125	−0.067
	(0.102)	(0.150)	(0.206)	(0.098)	(0.094)
HH Size	−0.088	−0.094	−0.086	−0.120[a]	−0.066
	(0.065)	(0.088)	(0.058)	(0.067)	(0.064)
Ag. Assets	0.552[a]	1.132[b]	0.463	1.167[c]	1.316[c]
	(0.334)	(0.466)	(0.373)	(0.364)	(0.434)
Distance, Weekly Market	−0.058[c]	−0.067[b]	−0.001	−0.026	−0.029
	(0.022)	(0.028)	(0.025)	(0.024)	(0.029)
# Farm Families	0.454[c]	0.193	0.018	0.169	0.301
	(0.157)	(0.181)	(0.127)	(0.151)	(0.203)
% Comm. Adopt, Mod.	0.878[b]	0.993[b]	0.303	0.542	1.443[c]
	(0.376)	(0.447)	(0.380)	(0.334)	(0.450)
% Comm. Adopt, High	0.186	0.568	0.532[b]	−0.022	1.005[b]
	(0.295)	(0.408)	(0.260)	(0.310)	(0.409)
Constant	−6.289[b]	−9.620[c]	−1.236	−1.584	−8.214[c]
	(2.739)	(3.701)	(2.281)	(2.724)	(3.141)
Log-Likelihood	−3847.22				
Pearson's Chi Square			65.68		
p-value	0.006				
Observations	1205				

Notes: the table displays the result from the coefficients of a weighted multinomial logit on the five adoption pathway categories of labor-intensive practices at household level, where Never Adopt is the baseline category. The pathways are defined by the adoption status of the respondent household captured in the three waves under study (2014, 2018, 2020). Full table of results are found in Table A2 in Appendix 1. Significance: Standard errors, in parentheses, are clustered at community level.
[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.

5.3.1. *Labor-intensive adoption*

5.3.1.1. SAPP beneficiaries are more likely to adopt labor-intensive practices suggesting effectiveness in information dissemination. As Table 3 shows, beneficiaries of SAPP are more likely to be adopters and always adopters of labor-intensive practices versus being never adopters. In terms of magnitude, the impacts are large; households are nearly three

[9] We have also computed the marginal effects of the explanatory variables on the probability of falling into a specific category versus any other category. Results are similar but with fewer significant variables. Thus, the explanatory variables are better able to distinguish between different categories of adoption versus never adoption, but are less able to discriminate amongst the different adoption categories. The latter is consistent with a dynamic adoption process for those who adopt.

times more likely to have adopted labor-intensive practices versus never adopters. This suggests that the project was successful at disseminating practically useful information on labor-intensive GAPs and facilitating learning from neighbors and demonstration plots.

5.3.1.2. Climate and agro-ecological factors are not strong determinants of labor-intensive adoption. Altitude significantly increases adoption probability and flexibility. The climate and agro-ecological variables have limited impact on adoption patterns for labor-intensive practices, with only a negative impact on adoption in areas prone to heavy rainfall. Instead, the probability of falling into all five adoption pathways is greater at higher altitudes. This is consistent with results found in Smith et al. (2016), who find larger soil fertility benefits on maize yields at higher altitudes, in part due to higher rainfall at higher altitudes. Moreover, the coefficient on flexible adoption is statistically significantly greater vis-à-vis other adoption pathways, indicating that the ability to adjust to current conditions – such as forecast of drought – is particularly valuable at higher altitudes.

5.3.1.3. Extension networks and agricultural assets increase adoption of labor-intensive practices. Greater access to extension agents reduce transaction costs of adoption, while neighbors' adoption has minimal impact on learning costs. The land and labor constraints, proxied by own rainy season landholdings and household size, do not have strong impacts on the labor-intensive adoption pathways chosen. However, agricultural assets do increase the probability of being an adopter, experimenter, dis-adopter and always adopter. The number of farm families within an extension planning area also favors all adoption pathways vis-à-vis never adopters, consistent with lower transactions costs of learning about labor-intensive practices. The coefficients on flexible adoption and experimenters are statistically larger than the coefficient on adopters, indicating that greater opportunities to connect with extension agents lowers costs of transient adoption. The proportion of community members who had adopted labor-intensive practices at baseline has limited impacts on adoption pathways chosen, outside of a strong impact distinguishing always adopters from never adopters. This suggests that neighbors' adoption patterns of labor-intensive practices do not significantly reduce transactions costs of learning about these practices and/or adapting to local conditions, and also that they do not necessarily lower the transactions costs of transient adoption.

5.3.1.4. Climate variability has limited impacts on the adoption of labor-intensive practices. Information dissemination is key for labor-intensive adoption, with higher altitudes and larger farm networks aiding adoption, while market distance and climate variability have little impact. To summarize in terms of our hypotheses, greater climate variability has limited impacts on the adoption of labor-intensive practices indicating either that these practices do not lower production loss risk or beneficiaries do not perceive them as such. Results suggest that the marginal benefit to adoption is greater at higher altitudes, but not necessarily on cropped land with soil limitations or of varying degree of slope. In terms of learning by experimenting, the coefficient on own land is only significant for adopters. In terms of learning by observing, the evidence suggests limited learning through the experience of neighbors' adoption decisions. Instead, being a SAPP beneficiary and being located where the network of farm families within and EPA is greater significantly increases pursing different adoption pathways versus never adopting. These results suggest that information dissemination through various pathways is particularly important to promote the adoption of labor-intensive practices. Being at higher altitudes and having larger farm family networks also favor dynamic paths of adoption. However, distance to market and climate variability have no significant impacts, whereas we hypothesized that both of these would decrease costs of transient adoption and increase the benefits from flexibility.

5.3.2. Land-intensive adoption

5.3.2.1. SAPP was not a strong determinant of land-intensive adoption. Agro-ecological factors like drought, rainfall, and altitude are strong predictors of adoption pathways. Table 4 presents the estimates obtained when running a multinomial logit on the categories of land-intensive adoption. In terms of treatment, SAPP had no significant impact on promoting any adoption pathway, indicating that information sharing and providing learning opportunities about land-intensive practices was less successful than for labor-intensive practices. Instead, the agro-ecological and climate conditions are stronger predictors of adoption pathways. Land-intensive practices are more likely to be adopted, flexibly adopted and always adopted in drought-prone areas, while those in areas more prone to heavy rainfall were more likely to be adopters. Altitude also favors adoption, flexible adoption and always adopt, which is consistent with greater threats of soil erosion at higher altitudes, and the fact that threats increase with weather events such as heavy rainfall and flooding (Li et al., 2017a,b).

5.3.2.2. Agricultural assets, proximity to market and to neighbors, drive land-intensive adoption paths. Similar to labor-intensive practices, household land and labor constraints have limited impacts on distinguishing any adoption pathway from never-adopters. The agricultural asset index is again a significant predictor of pursuing different adoption pathways, particularly for flexible adoption, dis-adoption and always adopt. Shorter distances to market increase the probability of both adoption and flexible adoption. The number of farm families increases the probability of adoption only, while the percentage of neighbors adopting land practices at baseline, both at moderate and high levels, increase the probability of adopting, flexible adoption, experimentation, and always adoption. This suggests that neighbors experiences with land-intensive practices provides greater opportunity to learn by observing than labor-intensive practices; and, that costs of transitioning in and out of adoption of land-based practices are also relatively lower when one can observe other farmers following a similar dynamic adoption pathway.

5.3.2.3. Being in drought-prone areas all adoption pathways for land practices are likely, while in heavy rainfall regions the most frequent is the adopter pathway. Higher altitudes support adoption and neighbors plays a key role. To summarize, for land-intensive practices, those located in drought prone regions are more likely to follow all adoption pathways versus never-adopters, while those located in areas prone to heavy rainfall are more likely to follow the adopter pathway. This suggests that land-intensive practices do lower production risks. Similar to labor-intensive practices, being located at higher altitudes also favors pursuing adoption pathways. With respect to learning by experimenting, the coefficient on own land is never significant, indicating that larger land sizes do not alone spur adoption or experimentation, though we note that land sizes are indeed quite small to start with. With respect to learning by observing, the percentage share of neighbors adopting is a strong predictor of pursuing adoption pathways. On the other hand, being a SAPP beneficiary has no statistically significant impact, while the number of farm families is only significant when distinguishing adopters from never adopters. These results suggest that learning by observing is particularly important for land-intensive practices. Flexible adopters are more likely to be located in drought-prone areas and closer to weekly markets, both consistent with our hypotheses. Flexible adopters are also more likely to be located at higher altitudes and in communities with moderate levels of adoption at baseline, and own more agricultural assets.

5.4. Heterogeneity: weather shocks

We next evaluated the extent to which treated households were more likely to follow certain adoption pathways if they were also more vulnerable to extreme weather events. To do so, we evaluate the marginal impacts of drought- and heavy rainfall-prone climate conditions when treated = 1 (beneficiaries) and treated = 0 (controls) for each of the six adoption pathways. Results are presented in Tables 5a, 5b, 6a and 6b. The first column contains the pathway and treatment status over which the margins are evaluated, the second column gives the marginal effect, the third column gives the p-value for the marginal effect, the fourth column gives the contrast between the marginal effects evaluated at 1 and 0, and the fifth column gives the p-value for the contrast. For labor practices, beneficiary households that are more exposed to droughts are more likely to be flexible adopters and experimenters than control households, as captured in Table 5a. This is consistent with the

Table 5
The role of Climate Conditions on Adoption Pathway of Labor-intensive Practices Evaluated by Treatment Status.

5a: Drought-Prone

Margin Effects of Drought-Prone at:	dy/dx	p-value for dy/dx	Contrast dy/dx	p-value for Contrast
Never Adopt, Control	0.031	0.466		
Never Adopt, Treated	−0.012	0.605	−0.044	0.375
Adopt, Control	−0.017	0.260		
Adopt, Treated	−0.045 [a]	0.090	−0.029	0.340
Flexible Adopt, Control	−0.019 [b]	0.039		
Flexible Adopt, Treated	0.017 [a]	0.067	0.036 [c]	0.005
Experimenter, Control	−0.037	0.214		
Experimenter, Treated	0.046 [c]	0.002	0.083 [b]	0.011
Dis-adopt, Control	0.013	0.637		
Dis-adopt, Treated	−0.019	0.481	−0.032	0.382
Always Adopt, Control	0.029	0.398		
Always Adopt, Treated.	0.014	0.500	−0.014	0.696

5b: High Rainfall-Prone

Margin Effects of Heavy Rainfall-Prone at:	dy/dx	p-value for dy/dx	Contrast dy/dx	p-value for Contrast
Never Adopt, Control	0.167	0.784		
Never Adopt, Treated	0.434	0.430	0.266	0.749
Adopt, Control	−0.315	0.213		
Adopt, Treated	−1.129 [c]	0.003	−0.814 [a]	0.076
Flexible Adopt, Control	0.093	0.622		
Flexible Adopt, Treated	0.525 [a]	0.059	0.432	0.173
Experimenter, Control	−0.441	0.283		
Experimenter, Treated	−0.181	0.601	0.260	0.624
Dis-adopt, Control	0.250	0.730		
Dis-adopt, Treated	0.168	0.721	−0.081	0.925
Always Adopt, Control	0.245	0.521		
Always Adopt, Treated.	0.183	0.663	−0.063	0.912

Notes: The table reports the marginal effects for categories of labor-intensive adoption. The upper panel, 5a, gives results for the marginal effects of being located drought-prone areas for treated and controls, while 5b provides information the same information but for heavy rainfall-prone areas. Significance.

[a] $p < 0.1$.
[b] $p < 0.05$.
[c] $p < 0.01$.

Table 6
The role of Climate Conditions on Adoption Pathway of Land-intensive Practices Evaluated by Treatment Status.

6a: Drought-Prone

Margin Effects of Drought-Prone at:	dy/dx		p-value for dy/dx	Contrast dy/dx		p-value for Contrast
Never Adopt, Control	−0.045	**	0.022			
Never Adopt, Treated	−0.008		0.635	0.037		0.160
Adopt, Control	−0.005		0.907			
Adopt, Treated	0.052	**	0.047	0.056		0.195
Flexible Adopt, Control	0.018		0.362			
Flexible Adopt, Treated	0.030		0.144	0.012		0.652
Experimenter, Control	−0.003		0.898			
Experimenter, Treated	−0.057	***	0.004	−0.053	*	0.085
Dis-adopt, Control	−0.022		0.286			
Dis-adopt, Treated	−0.037	**	0.016	−0.015		0.522
Always Adopt, Control	0.056	*	0.063			
Always Adopt, Treated.	0.020		0.442	−0.036		0.325

6b: High Rainfall-Prone

Margin Effects of High Rainfall-Prone at:	dy/dx		p-value for dy/dx	Contrast dy/dx		p-value for Contrast
Never Adopt, Control	−0.802	***	0.007			
Never Adopt, Treated	0.420		0.260	1.222	***	0.009
Adopt, Control	1.283	***	0.008			
Adopt, Treated	1.140	**	0.027	−0.144		0.836
Flexible Adopt, Control	0.037		0.906			
Flexible Adopt, Treated	−0.615		0.231	−0.652		0.266
Experimenter, Control	−0.259		0.427			
Experimenter, Treated	−0.378		0.373	−0.120		0.816
Dis-adopt, Control	−0.867	***	0.001			
Dis-adopt, Treated	0.277		0.472	1.144	**	0.011
Always Adopt, Control	0.608		0.211			
Always Adopt, Treated.	−0.843	*	0.062	−1.451	**	0.024

Notes: The table reports the marginal effects for categories of labor-intensive adoption. The upper panel, 6a, gives results for the marginal effects of being located drought-prone areas for treated and controls, while 6b provides information the same information but for heavy rainfall-prone areas.

learning from project activities and also with greater relative benefits to transient adoption in drought-prone locations. However, beneficiaries in areas subject to heavy rainfall events were less likely to adopt labor-intensive GAPs than control households, as captured in Table 5b.

Table 6a presents results for the marginal impacts of drought on land-intensive GAP adoption pathways. The only significant impact shows that beneficiary households were less likely to be experimenters in drought-prone locations vis-à-vis control households. Marginal impacts of being located in heavy rainfall-prone areas, captured in Table 6b, suggest that beneficiaries were actually more likely to never adopt and to dis-adopt, and less likely to be always adopters. It may be that the project promoted other mechanisms to manage heavy rainfall, though we could not identify what those might be. Overall, results suggest that the project was not able to spur additional adoption in areas more exposed to extreme weather conditions, which are likely to become more frequent and intense due to climate change (Huber and

Gulledge, 2011).

5.5. Robustness checks

A first test consists in redefining the categorical adoption pathways around their potential outcomes, rather than the main constraints to adoption. In particular, while all labor-intensive practices are related to soil fertility management, land-intensive practices include soil fertility trees. We create a soil fertility category that includes all labor-intensive practices plus fertility trees, and a soil and water conservation category includes all of the land-intensive practices except fertility trees. Results are reported in Tables A3 and A4 in Appendix 2, and are substantially similar to results found in Tables 3 and 4 As a second test, we merge together experimenters with dis-adopters, and flexible adopters with adopters, thus passing from six to four adoption categories. Tables A5 and A6 in Appendix 3 report the results for the labor-intensive and land-intensive categories, which remain consistent results found in Tables 3 and 4

6. Concluding comments

This paper aims at contributing to the understanding of factors associated with the dynamics of adoptions decisions given households constraints, agro-ecological characteristics and climatic patterns. To this purpose we used a unique three-period panel dataset constructed to evaluate the impacts of a project promoting sustainable agricultural development through “good agricultural practices” in Malawi. Noting that many previous projects had limited success in promoting similar practices, we focused on the determinants of adoption pathways documented over the three survey waves. To conduct a more systematic analysis of the dynamic of adoption we used adoption pathway trees differentiating types of adoption pathways based on the intensity of labor or land required. The pathway trees are presented in Fig. 1a and b and clearly highlight how and to what extent the adoption decision is dynamic for both labor and land practices, given that overall only a relatively small percentage of the total sample never adopt (23% for land and 35% for labor). The decision tree also suggests that households are more likely to be constrained by labor than by land, since labor-intensive practices have a higher percent of never adopters and lower percent of always adopters compared to land-intensive practices.

Results from the multinomial logit estimations suggest that there are some general factors influencing both types of adoption pathways – labor or land intensive - but also significant differences in the factors that drive the two types of adoption pathways. For instance, climate and agro-ecological characteristics do not have a significant impact on distinguishing different adoption pathways from never adoption for labor-intensive, outside of altitude. Instead, information dissemination and wider learning opportunities – either through the SAPP project or through greater availability of extension – have significant impacts on adoption, including flexible adoption and experimentation. Learning by observing neighbors did not increase the likelihood of pursuing an adoption pathway vis-à-vis never adopters. On the other hand, with respect to land-intensive adoption, being located in drought-prone and heavy rainfall-prone areas significantly increased the probability of being an adopter, and always adopter. On the other hand, access to information and learning opportunities had limited impacts; the SAPP project did not significantly influence adoption decision, whereas the number of farm families only increased the probability of being an adopter. Instead learning by observing, proxied by proportion of households in the community adopting land-intensive practices at baseline, was significantly increased the likelihood of all adoption pathways vis-à-vis never adoption. For land-intensive practices, then, learning by observing was more effective than learning by experimenting or learning through information dissemination. For both labor- and land-intensive practices, higher altitudes and more agricultural assets favored both adoption and transient adoption. And, for land-intensive practices, being located in a drought prone area, being located closer to market and where there are greater opportunities to learn all favored flexible adoption, consistent with higher marginal benefits and lower marginal costs of transitioning in and out of adoption as hypothesized.

Overall, our results suggest that households need flexibility in their choices, both when they are labor-as well as when they are land-constrained. It is also clear that access to information is critical to the adoption decision, though learning about different GAPs may be more successful through different learning mechanisms. It would appear that the SAPP project was relatively more successful at spurring labor-intensive adoption through information dissemination, but less able to generate significant amount of learning by observation to spur adoption of land-intensive practices.

The fact that adoption of GAPs is dynamic has implications both for the types of GAPs promoted and how they are promoted but also on designing projects that support adoption while recognizing that flexibility in adoption status is of value to smallholders. Additionally, our results suggest that taking a snapshot of adoption at one period of time may portray a too pessimistic picture of adoption and lead to the wrong conclusions. This is highlighted by the decision tree; at baseline, 54% and 56% did not adopt land- and labor-intensive practices, respectively; but, only 23% never adopted any land-intensive practices and only 35% never adopted any labor-intensive practices at endline.

The literature cited above notes that for many land-intensive practices, benefits do not accrue until at least three years or more of continuous adoption. For instance, the SAPP project did promote conservation agriculture (minimum soil disturbance, permanent ground cover and crop rotation), which many proponents argue must be continuously adopted for at least 3–5 years to reap the full benefits (Giller et al., 2009). In 2020, less than 1% of households practiced minimum soil disturbance, and no one practiced all three. Fortunately, SAPP promoted a range of other practices as well.

Our results also highlight the important role played by information and its diffusion in spurring the adoption decision, thus, contributing to a growing but still limited literature on effective information dissemination strategies. In particular, our results suggest that labor-intensive practices may well be amenable to less costly dissemination strategies through agricultural extension-based digital media campaigns to help increase the “availability” of extensionists. Land-intensive practices, however, require greater visual transmission of knowledge and a clear pathways and timeline for benefits to accrue compared to the investments made and the constraints faced.

The results of the analysis presented in this paper offer a strong support to more effective project design and investment strategies that promote suitable good agricultural practices (GAPs), considering land, resource, and labor constraints, as well as areas affected by weather shocks and climate variability. Specifically, analysis suggest that tailored support is crucial for drought- and rainfall-prone areas where land-intensive practices are more likely to succeed with better access to extension services and learning by observing. Investments and policies should, thus, focus on providing targeted support mechanisms, such as incentives for land-intensive practices and enhancing demonstration opportunities and extension agent presence. The same applies in higher altitudes where land intensive adoption is more likely. For labor-intensive practices, which are more flexible, easier access to micro-credit or rotating grants could facilitate transient adoption and adaptation.

With respect to limitations of the analysis, though we were able to use a three-period panel dataset to perform our analysis, which is a step in the right direction, one would optimally like to have access on adoption decisions over more time periods. In Malawi, there is one main growing season, which means data covering more than three years. In other contexts, there are more growing seasons within the year, which may make data collection less costly. Alternatively, for project impact assessments, short surveys on adoption on a yearly basis would help augment information gathered in the baseline, midline and endline surveys. We have also aggregated different adoption decisions into land and labor intensive categories, and though results are similar if aggregating by benefits (soil fertility, soil and water conservation), this choice is mainly driven by limited adoption of a wide range of more specifically defined practices. Further research is needed to better conceptually ground the choice of aggregation in specific contexts. Finally, more evidence is needed to understand the value of flexibility in adoption choices over time and the implications for project development, particularly given the likely increase in the frequency and severity of weather extremes.

CRediT authorship contribution statement

Nancy McCarthy: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Giuseppe Maggio:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Romina Cavatassi:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Giuseppe Maggio reports financial support was provided by Italian Ministry of University and Research. Giuseppe Maggio reports a relationship with Italian Ministry of University and Research that includes: funding grants. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.122636.

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