Original research article

Rainfall forecasts, learning subsidies and conservation agriculture adoption: Experimental evidence from Zambia

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ABSTRACT

Adapting smallholder rainfed farming systems to climate change requires adoption of technologies that build resilience to climate shocks. One such technology is conservation agriculture, yet its adoption by smallholders in Southern Africa is not widespread. We use incentivized economic field experiments in Zambia to test, ex-ante, whether providing rainfall forecasts and a time-bound learning subsidy can help increase the adoption of conservation agriculture. We found that providing rainfall forecasts predicting low rainfall significantly increased the probability of adopting conservation agriculture by 8 percentage points, while offering a subsidy increased the chances of adoption by 11 percentage points. Bundling rainfall forecasts and subsidies did not significantly influence adoption, perhaps because these were not complementary. Having experienced normal rainfall in the previous experiment round (cropping season) was associated with 6 percentage points higher odds of adopting conservation agriculture, while past exposure to low rainfall significantly reduced the probability of adoption by 6 percentage points. These results suggest that farmers do not expect two subsequent seasons to be the same given the increase in rainfall variability in the region. Other important drivers of adoption are hosting demonstration plots and education level of the participant. These findings provide evidence that providing rainfall forecasts and time-bound learning subsidies may be effective ways to enhance the adoption of conservation agriculture in Zambia and imply a need to reframe conservation agriculture as means to address low and erratic rainfall. Future research can evaluate the persistence of such effects using randomized controlled trials.

Practical implications

Sub-Saharan Africa remains among the most exposed and vulnerable regions to climate change because of the high dependence on rainfed agriculture. This makes it necessary for farmers to adopt climate resilient farming options such as conservation agriculture based on three integrated principles of minimum tillage, crop residue retention and crop diversification through rotations or intercrops. Despite demonstrated biophysical, environmental and economic benefits associated with conservation agriculture, its uptake among smallholder farmers remains limited in the region. Although southern Africa has had sustained promotion of conservation agriculture, it is often argued that the current adoption levels are not commensurate with the levels of

investments in promotion. This has raised policy interest to (re)-examine (a) drivers and barriers of adoption, and (b) what can be done to improve the adoption of promising CA practices among smallholder farmers.

The low adoption of conservation agriculture despite its benefits presents a conundrum in international development and has sparked interest to identify nudges and incentives for adoption as highlighted in (b) above. We consider two policy options: subsidies and rainfall forecasts. Conditional subsidies have the potential to increase the adoption of conservation agriculture. This is demonstrated by the *Pfumvudza* program in Zimbabwe where farmers access subsidized inputs on condition that they dedicate a given amount of land to conservation agriculture. The *Pfumvudza* program has dramatically increased CA adoption to more than 90 % among smallholder farmers in Zimbabwe. Whether this adoption can be sustained is an interesting question for future research.

However, because most national subsidy programs in southern Africa are not designed to incentivize the adoption of conservation agriculture, the effects of subsidies on adoption remain unclear. While conservation agriculture is perceived more beneficial in low rainfall environments, the effects of providing seasonal or near-term, e.g., 10-day rainfall forecasts on adoption remains understudied.

This paper contributes towards improving our understanding of what can be done to incentivize or nudge adoption of conservation agriculture in sub-Saharan Africa. We test two hypotheses. First, we test whether prior knowledge about below normal rainfall induces farmers to adopt water conserving conservation agriculture practices in the short-term. Second, we test if providing farmers with a learning subsidy that allows them to acquire requisite implements and inputs can nudge adoption of conservation agriculture, a technology that farmers would otherwise not adopt. For context, a learning subsidy is time limited and given to farmers to enable them to try out new agricultural technologies that they would otherwise not be interested or able to invent in. We study these effects *ex-ante,* using an incentivized lab-in-the field framed economic experiment conducted with 89 smallholder farmers exposed to conservation agriculture in five districts of Zambia. Each participant played four experimental sessions or 'seasons' for a total of 356 observations.

Participants in the experimental adoption sessions chose between conservation and conventional agriculture at the start of the farming season, given the relative returns to each farming option under normal and below normal rainfall. The returns in the adoption experiments were different depending on whether the rainfall was normal (good) or below normal (low). In line with the terminology of the Zambia Meteorological Department (ZMD), good or normal rainfall in the experiments corresponded to normal rainfall defined as rainfall between 75 % and 125 % of the average for the reference period 1981 to 2020 growing seasons (October, November and December, January, February, and March), while low rainfall referred to below normal rainfall, which is rainfall less than 75 % of the average for the reference period 1981 to 2020 growing seasons (October, November and December, January, February, and March). Whether the rainfall was normal or below normal was only determined after all participants had chosen the farming option (either conservation agriculture or conventional) for a season. To account for increasing rainfall variability, there was a 25 % chance that the seasonal rainfall was normal and a 75 % chance that rainfall was below normal.

There are three main findings: First, as would be expected, the majority (93 %) of participants chose conservation agriculture, while 7 % chose conventional agriculture in the first round without any incentives. Introducing a learning subsidy for conservation agriculture in the second session changed farmer choices, with 85 % choosing conservation agriculture with the subsidy, 13 % chose conservation agriculture only and 1 % chose conventional agriculture. In the third session with seasonal rainfall forecast, 81 % chose conservation agriculture with seasonal forecast, 3 % chose conservation agriculture alone, 10 % chose conventional agriculture with seasonal forecast and 6 % chose conventional agriculture. In the last session, 80 % chose conservation agriculture with both seasonal forecast and subsidy, 12 % conservation agriculture only, 7 % conservation agriculture with seasonal forecast and 1 % chose conventional agriculture. The main take away message here is that introducing incentives in form of subsidies and rainfall forecast influenced farmers' adoption decisions with most of the farmers opting for conservation agriculture associated with the incentives. These findings highlight the potential positive influence of incentives on technology adoption.

Second, after controlling for several confounding factors within a multivariate regression framework, we found that providing seasonal rainfall forecast predicting below normal seasonal rainfall significantly increased the probability of conservation agriculture

adoption by 8 percentage points. Offering a subsidy increased the chances of adopting conservation agriculture by 11 percentage points. Third, having experienced normal rainfall in the previous experiment round (or 'season') was associated with 6 percentage points higher odds of adopting conservation agriculture, while past exposure to low rainfall significantly reduced the probability of adoption by 6 percentage points. These results suggest that farmers did not expect two subsequent seasons to be the same given the high rainfall variability in the region. As such, normal rainfall in the last season induced farmers to expect the opposite in the current season and vice versa. This in turn dictates farmers' choices of farming practices.

The findings have implications for climate services. We provide evidence that providing timely rainfall forecasts can be an effective way to nudge or incentivize the adoption of conservation agriculture. The key is to provide these forecasts timely, prior to the start of the rainy season and before farmers make up their minds on what cropping systems or farming options to follow. For southern Africa, this should not be later than October. Rainfall forecasts can be inherently technical given their probabilistic nature. As demonstrated in this paper, there is value in presenting these in simpler language that is accessible to farmers but retains the intended meaning. There is need to improve the accuracy of the rainfall forecasts to build farmers' confidence and trust in the estimates. This is especially important because farmers tend to update their beliefs about expected rainfall and therefore, benefits, based on past experiences. As such providing inaccurate forecasts, as has been the case in some countries in the region, would erode farmer confidence. Overall, the findings in this paper imply a need to reframe the promotion of conservation agriculture as means to address low and erratic rainfall. This suggests that climate services should go a step further to help farmers identify suitable adaptation options depending on the predicted weather. A good entry point is to bundle the promotion of conservation agriculture with rainfall forecasts to help farmers make better informed adoption decisions. This is especially important given the varying agroecologies with different rainfall regimes across countries in southern Africa.

Introduction and background

Climate change and livelihoods are intertwined in sub-Saharan Africa where 55 – 62 percent of the workforce depend on rainfed agriculture (Ipcc, 2022). The high dependence on rainfall for crop production exposes the region to climate shocks. Conservation agriculture (CA) based on minimum soil disturbance, crop residue retention and crop diversification amongst other good agriculture practices is one viable technology to build climate resilient smallholder farming systems, hence it is the focus of this study. The biophysical and to some extent climate, environmental and economic benefits of conservation agriculture systems are well established (Abdulai, 2016; Abdulai and Abdulai, 2016; Tambo and Mockshell, 2018; Thierfelder et al., 2017; Thierfelder et al., 2015; Jaleta et al., 2016; Mupangwa et al., 2016; Pannell et al., 2014). Conservation agriculture offers opportunities for smallholder farmers to raise productivity while building resilience to shocks in rainfed smallholder farming systems (Thierfelder et al., 2017; Komarek et al., 2021). Overall, the weight of the evidence suggests that CA is climate-smart and can help farmers build resilience to low rainfall stress (Tesfaye et al., 2021; Thierfelder et al., 2017).

However, results are context specific, highlighting that the drivers of adoption and impacts of CA are heterogenous (Andersson and D'Souza, 2014; Arslan et al., 2022; Arslan et al., 2014; Corbeels et al., 2020; Giller et al., 2009; Pannell et al., 2014). Despite the optimism on CA, there are concerns that current adoption is not commensurate with the levels of investments in promoting CA in southern Africa (Arslan et al., 2014; Corbeels et al., 2020; Pannell et al., 2014; Tufa, Kanyamuka, et al. 2023). This perception has raised policy interest to (re)-examine (i)

drivers and barriers of adoption, and (ii) what can be done to improve the adoption of promising CA practices among smallholder farmers.

Recent *meta*-analyses and reviews on the drivers of adoption and impacts of agricultural technologies, including CA practices in sub-Saharan Africa and Asia (Arslan et al., 2022; Jain et al., 2023) found that access to information, wealth, and institutional factors such as membership to farmer groups, social capital and tenure are strong drivers of adoption. Pangapanga-Phiri et al. (2024) found that stronger extension support and experiential learning through farmer hosted demonstrations were the main key drivers of sustained CA adoption in Nkhotakota district of Malawi. While many farmers are aware of CA in southern Africa, fewer have adopted, and dis-adoption in high. Tufa, Kanyamuka, et al. (2023) estimated that about 60 % of farmers interviewed that had adopted minimum tillage in Malawi dis-adopted it, compared to 19 % in Zambia and 3 % in Zimbabwe. Authors also found that there are largest gaps between awareness and adoption highlighting that being aware of CA does not necessarily translate into adoption. On the other hand, authors found smaller gaps between demonstration and adoption, and training and adoption, signifying the important roles played by experiential learning in the adoption process. The main drivers of non-adoption and dis-adoption included limited technical knowledge, lack of interest/incentives to invest in CA, risk aversion, impatience, short planning horizons which do not align with CA whose benefits are realised after 2 – 5 cropping season, limited access to credit to purchase requisite inputs and implements, labor intensity of some CA elements, and limited access to herbicides or mis-use of herbicides (Ngoma et al., 2021; Pangapanga-Phiri et al., 2024; Pannell et al., 2014; Thierfelder et al., 2024; Tufa et al., 2023; Ngoma et al., 2024).

Risk and time preferences are important drivers of adoption, whose role in the adoption of agricultural technologies have been studied since the 1980s. Seminal papers by Feder (1980), Feder et al. (1985) and Binswanger (1981) show that there is an inverse relationship between the adoption of new agricultural technologies and risk aversion. In the face of risk and uncertainty, farmers avoid technologies they perceive as risky. Recent papers on the subject include (Brick and Visser, 2015) where it was found that risk-averse farmers chose traditional maize varieties compared to improved varieties in South Africa. Similarly in Malawi, (Holden and Quiggin, 2017) found a strong correlation between risk-aversion and the adoption of drought-tolerant maize and local maize varieties against improved maize varieties. However, a positive correlation is expected between risk and loss aversion, and the adoption of new seed varieties that are perceived as risk reducing (Ward and Singh, 2015). Time preferences on the other hand imply that impatient farmers would be more likely to prioritize short-term gains. Few available studies show that there is a negative correlation between CA adoption, and risk and time preferences in southern Africa (Simutowe et al., 2024; Tufa, Alene, et al. 2023).

Although access to subsidies is expected to improve access to complementary inputs, most national subsidy programs are not designed to incentivize CA adoption and the effects of subsidies on adoption remain unclear. An exception is the *Pfumvudza* program in Zimbabwe where farmers access subsidized inputs on condition that they dedicate a given amount of land to CA (Mavesere and Dzawanda, 2022). This has dramatically increased CA adoption in Zimbabwe to more than 90 %. Whether this adoption is sustainable beyond the subsidy will be an interesting area of future study. Access to subsidized inputs can spur CA adoption. For example, Tufa, Kanyamuka, et al. (2023) found that farmers that accessed subsidized inputs were more likely to use mulching in Malawi, minimum tillage and mulching in Zambia and all the three CA elements in Zimbabwe.

While CA is generally perceived to be more beneficial in low rainfall environments, e.g., (Michler et al., 2019; Pannell et al., 2014; Tesfaye et al., 2021), the effects of providing seasonal or near-term, e.g., 10-day rainfall forecasts on CA adoption remains understudied. This paper contributes towards filling this gap and aims to answer questions around what can be done to incentivize or nudge adoption of full CA in sub-

Saharan Africa. We consider information as an input into production and study how providing seasonal rainfall forecasts prior to the start of a growing season and 'learning' subsidies affect farmers' decisions to use CA. We consider only short-term adoption of CA.

In essence, we test two hypotheses. First, we test whether prior knowledge about below normal rainfall induces farmers to adopt CA in the short term. This is borne from findings that past weather realizations influence farmers' current farming decisions and that past experiences with technologies form the basis for future expectations (Sesmero et al., 2017; Foster and Rosenzweig, 2010). We postulate in the second hypothesis that providing farmers with a learning subsidy that allows them to acquire requisite implements and inputs can nudge adoption of technologies that farmers would otherwise not adopt. A learning subsidy is one given to induce farmers in this context, to try out new agricultural technologies that they would otherwise not be interested or able to invent in. In this sense, a subsidy can induce short-term adoption through learning effects, e.g., (Omotilewa et al., 2019). We study these effects *ex-ante,* using an incentivized lab-in-the field framed economic experiment conducted with smallholder farmers exposed to CA in five districts of Zambia. We use the term experiment in this paper to refer to a collection of sessions where farmers completed specific activities.

Several authors have studied different aspects of CA adoption using economic or lab-in the field experiments. In Malawi, (Maertens et al., 2021) used a quasi-randomized controlled trial and found that farmers exposed to demonstrations for the whole season had stronger intentions to adopt than those who only attended field days. (Ward et al., 2018) and (Bell et al., 2018) found that providing subsidies and payments for ecosystem services in an economic field experiment improved the adoption of CA and other land management practices in Malawi. Another somewhat related study is that of (Oyinbo et al., 2022) who evaluated the impacts of agro-advisories for site-specific fertilizer recommendations and information on a range of outcomes in Nigeria. Using randomized controlled trials, (Oyinbo et al., 2022) found that providing agro-advisories increased adoption of fertilizer management practices by 2–15 %, fertilizer use by 25 %, maize yield by 19 % and net revenue by 14 %. Providing a one-time subsidy for hermetic bags to farmers in Uganda in a randomized controlled trial resulted in 5 percentage points increase in the probability of beneficiaries buying these bags from commercial sources (Omotilewa et al., 2019).

We add to these studies in two main ways. First, to the best of our knowledge, this is the first paper to explicitly link provision of a negative seasonal rainfall forecast to adoption of CA using an incentivized economic field experiment. Second, our framed field experiments allow us to study the bundled effects of seasonal rainfall forecasts and learning subsidies in one setting. Because farmers are likely to respond differently to current and past weather events, we also controlled for past rainfall in addition to the seasonal forecast. Zambia is suitable for this study given the long history of promoting CA and the increasing rainfall variability (Hamududu and Ngoma, 2019).

Conceptual framework

Farmer decisions to adopt CA can be motivated using the learning model developed by (Foster and Rosenzweig, 1995) and (Foster and Rosenzweig, 2010), and applied by others, e.g., (Maertens et al., 2021). The main thesis of this learning model is that technology adoption is a function of experience, beliefs about the new technologies and learning. It postulates that learning happens when information alters the behavior of the recipient in ways that increases private benefits. Past experiences, whether positive or negative, influence belief formation about technologies and ultimately the expected benefits from adoption. Past experiences can be in terms of technologies (Foster and Rosenzweig, 2010; Maertens et al., 2021) or in terms of weather events (Sesmero et al., 2017; Mulenga et al., 2017).

According to (Maertens et al., 2021), farmers decide whether to adopt CA or not in two steps. First, farmers form beliefs about potential

Table 1
Sample distribution by agricultural camp for each experiment.

		Mother host farmer	Baby host farmers	Other farmers	Number male	Total
Chinjara		2	4	6	7	12
Kapichila		3	4	6	5	13
Mboole		3	7	7	6	17
Simaubi		7	4	5	9	16
Dumba		2	6	6	7	14
Namakube		6	4	7	14	17
Total	n	23	29	37	48	89
	(%)	25.8	32.6	41.6	54	100

or expected benefits from CA in comparison to alternatives e.g., conventional agriculture. This is often based on past experiences with CA whether directly through experiential learning or by observing from neighbors/peers. Once a farmer decides to use CA, they invest to learn about it. As such, this step is incomplete without experience and/or learning. Once beliefs are formed, farmers then decide whether to adopt CA based on perceived benefits, knowledge, and cultural factors.

Farmers may fail to adopt CA or dis-adopt it if they (i) are not aware of the potential benefits because they have no experience or limited technical information, (ii) are risk averse and/or impatient, (iii) have short term planning horizons and high discount rates, (iv) have limited access to finance to purchase requisite inputs and implements, or (v) fail to optimally manage it to maximize returns (Pangapanga-Phiri et al., 2024; Pannell et al., 2014; Tufa et al., 2023).

The role of risk and time preferences in technology adoption is crucial. However, there are few studies with contrasting results specific to CA. Tufa, Kanyamuka, et al. (2023) found that risk aversion was correlated with a lower likelihood of farmers adopting minimum tillage in Zambia and Zimbabwe. It was also associated with a reduced likelihood of adopting mulch in Malawi and Zimbabwe, and rotation in Zambia. Authors concluded that farmers that adopted CA tended to be less risk averse and less impatient. Similarly, (Simutowe et al., 2024) found that risk and time preferences reduced the probability of adopting minimum tillage alone and in combination with other CA elements by at least 3 percentage points on the extensive margin and reduced the intensity of adoption by 0.02 – 0.22 ha. These results are crucial because benefits from CA are often realized in the medium to long-term (Montt and Luu, 2020) and learning becomes very important.

In lieu of experience, learning through extension and from peers can help farmers learn about CA. The significance of experiential learning in the adoption of knowledge intensive technologies like CA is important to give farmers a chance to engage in hands-on practice in addition to theory. There is evidence of this in (Maertens et al., 2021) who found participation in season-long demonstrations increased farmers' intentions to adopt improved practices in Malawi. Fisher et al (Fisher et al., 2018) and Holden et al., (Holden et al., 2018) found that farmer-to-farmer extension approaches such as the lead farmer model is important in increasing awareness of CA among follower farmers in Malawi. In addition, experiential learning through demonstrations and dedicated extension staff were important factors that drove up CA adoption in Nkotakota district, a CA sentinel site in Malawi, and for the general rise in CA adoption in southern Africa (Pangapanga-Phiri et al., 2024; Tufa et al., 2023).

Information provided through seasonal rainfall forecasts can play a crucial role in influencing farmers' decisions to adopt CA because farmers are able to form expectations about future benefits. If the new technology is costly or if its benefits accrue in the medium to long-term like CA (Montt and Luu, 2020; Pannell et al., 2014), learning subsidies are important to buffer the risks associated with crop failure and can enable farmers to access and experiment with new technologies. In addition, learning subsidies enable farmers to access and experiment with the technologies they would otherwise not afford or try while

covering farmers from production risks. If such subsidies are not available, farmers may fail to try CA and may opt to go with the familiar old technologies even when returns to the new technology are positive and higher. Even if there are possibilities for peer learning, some farmers may wait until peers have gained sufficient experience with CA before deciding to adopt. This may significantly delay adoption and development. This paper tests the effects of providing seasonal rainfall forecasts and learning subsidies, *ex-ante*, using incentivized low-cost, economic lab-in-the field experiments in Zambia.

Methods and data

Data and sampling procedures

The economic field experiments were conducted in 6 out of the 18 research agricultural camps under the Sustainable Intensification of Smallholder Farming Systems in Zambia (SIFAZ) project. Camps are the smallest administrative units in Zambian agriculture. The experiments were conducted in Chinjara and Kapichila camps in Eastern Province and in Simaubi, Namakube, Mboole, and Dumba camps in Southern Province. The experiments were conducted as part of the 2022 socioeconomic survey aimed to study CA adoption incentives for the 2021/2022 farming season. In each camp, we randomly sampled 3 – 7 mother trial host farmers, 4 – 7 baby trial host farmers, and 5 – 7 other farmers to participate in the experiments for a total of 89 participants, of which about 54 % were male (Table 1). Twelve experimental sessions, each with about 6 – 8 participants and lasting about 2 hours, were conducted in the study sites. About 2 sessions were conducted per day per camp. Mother host farmers host on-farm research trials, managed by researchers and extension that include 5 – 10 sub-plots showcasing different sustainable intensification practices, while baby host farmers are offshoots from mothers and showcase only one or two technologies on their own farms. The sampling frame was drawn from farmers randomly selected for the 2022 SIFAZ survey. Using a within subject design, each participant played all the four sessions for a total of 356 observations.

Adoption experiment procedures and framing

The framed economic field experiment included four sessions where farmers, in principle, chose between CA and conventional agriculture. The later sessions introduced specific policy instruments as explained below. We used a within subject design so that each person played all the four sessions. Unlike typical lab-in-the field economic experiments which can be hypothetical, we consider ours framed economic field experiments because CA and conventional agriculture practices were framed using large pictures pasted on walls or trees at the venue of the experiments. This added context to the experiments.

We defined CA adoption as allocating at least 100 % of a household's maize area to CA. As such, households adopting CA in the adoption experiments committed to allocating at least 1 hectare (ha) to maize production under full CA (minimum tillage (ripping, basins and/or zero tillage), rotation and mulch). Conventional agriculture was defined as the use of hand-hoeing and/or ploughing. The fact that the experiments were done in areas where farmers were familiar with CA helped to simplify explanations. Participants in the adoption sessions chose between CA and conventional agriculture at the start of the farming season, given the relative returns to each option under normal and below normal rainfall. These relative returns were based on gross margin per ha for maize[1] for the 2020/2021 season obtained from Chinjara, Kapichila, Simaubi, Namakube and Dumba camps where the activity was conducted.

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[1] Gross margins tables were given out to farmers and pasted on the walls to help with explanations.

Table 2
Payoffs for all experiment sessions played.

Experiment	Rainfall realization	
	Good (Normal) pay off (ZMW)	Bad (Low) pay off (ZMW)
Base session		
Conventional agriculture	27	11
Conservation agriculture	27	19
Subsidy session		
Conventional agriculture	27	11
Conservation agriculture	27	19
Conservation agriculture with subsidy	31	22
Rainfall forecast session		
Conventional agriculture	27	11
Conservation agriculture	27	19
Conventional agriculture with rainfall forecast	30	10
Conservation agriculture with rainfall forecast	30	21
Subsidy and rainfall forecast session		
Conventional agriculture	27	11
Conservation agriculture	27	19
Conventional agriculture with rainfall forecast and subsidy	30	10
Conservation agriculture with rainfall forecast and subsidy	34	25

Notes: The payoffs are based on actual maize gross margins per ha divided by 100 in Zambian Kwacha. Each participant won on average about USD 4 from the experiments.

The main difference between CA and conventional agriculture is in the tillage and management systems employed, but both can use fertilizers and improved seed. The payoffs (returns) in the adoption experiments were different depending on whether the rainfall was normal (good) or below normal (low). Normal rainfall was defined as the expected average rainfall per season that promotes optimal plant growth or what is often called normal rainfall. Low rainfall is characterized by below average rainfall that results in seasonal droughts and compromises crop growth. In the terminology of the Zambia Meteorological Department (ZMD), good or normal rainfall in the experiments corresponded to normal rainfall defined as rainfall between 75 % and 125 % of the average for the reference period 1981 to 2020 growing seasons (October, November and December, January, February, and March), while low rainfall refers to below normal rainfall, which is rainfall less than 75 % of the average for the reference period 1981 to 2020 growing seasons.[2] Because ZMD provides forecasts to farmers, we simplified the language to make it easier for farmers to follow, without loss of the intended message. We did not explicitly consider abnormally high rainfall in the experiments, which would fit into the category of above normal as rainfall greater than 125 % of the average for the reference period 1981 to 2020 growing seasons . Such high rainfall can be detrimental for optimal crop growth and CA would be less suitable.

Whether the rainfall was normal or below normal was only determined after all participants had chosen the farming option (either CA or conventional) for a season. To account for increasing rainfall variability (see Fig. 3 and (Ipcc, 2022)), there was a 25 % chance that the seasonal rainfall was normal. We used a 25 % chance which is lower than the proposed 50 % chance of a correct forecast for 10-day periods or longer.[3]

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[2] https://www.mgee.gov.zm/wp-content/uploads/2023/10/Seasonal-Rainfa ll-Forecast-for-the-20232024-Season.pdf — last accessed 18 May 2024.
[3] https://scijinks.gov/forecast-reliability/.

Because we provided seasonal forecast, we chose to be conservative. Future research can vary the probabilities for correct forecast but it seems that changing the percentage of correct forecast does not change farmer choices (Grothmann and Patt, 2005).

Payoffs used in these experiments for normal rainfall years are based on actual per ha maize gross margins for CA and conventional agriculture computed from mother and baby trial host farmers in 5 camps (2 in Eastern and 3 in Southern provinces). For below normal rainfall years, we assumed that yield declined by 30 % under CA and 60 % under conventional agriculture. These yield reductions are close to observations from previous experiments, e.g. (Mupangwa et al., 2017) and (Nyagumbo et al., 2020), and projected maize yield reductions due to climate change under conventional agriculture in SSA e.g., (Lobell et al., 2008).

There were three treatments added to the experiment sessions: *green (learning) subsidy*, seasonal *rainfall forecast information*, and a *combination of seasonal rainfall forecast and green subsidy*. These experiments build on Ngoma et al. (Ngoma et al., 2018) by using seasonal rainfall forecast instead of insurance, and by bundling seasonal rainfall forecast and green subsidies. Each session is explained in detail below. Once all the participants had made their choices in each of the four-adoption experiment sessions, and rainfall outcome had been determined for each, we randomly selected one session for payment. Learning, anchoring, or order effects are huge challenges in lab-in-the field economic experiments that use within-subject design as in our case. We used several strategies to minimize the effects. First, we randomized the order in which the sessions were played by different groups. Second, to minimize learning, we played practice rounds for as long as was necessary to ensure that all participants were comfortable with the procedures. Third, all experiment instructions were given in local language and repeated for as long as was necessary prior to the start of the experiments. Lastly, once the sessions were running, there was no communication allowed. We explain below additional analytics performed to check the robustness of the results.

Control or base sessions

Participants in the sessions were randomly selected from a random sample of farmers interviewed under the 2022 SIFAZ socioeconomic survey (more under sampling). Ethical approval for field work was provided by ERES Converge IRB, reference number 2021-May-099.[4] Everyone played a base or control adoption session where they chose between CA and conventional agriculture at the start of a farming season without any additional treatments. The returns to CA and conventional agriculture with normal seasonal rainfall were equal at K27 (United States Dollar [USD] 1.5) per hectare.[5] With below normal seasonal rainfall, returns were *K*11 for conventional agriculture and K19 for CA (Table 2). Note that the actual amounts are a factor of 100 of the amounts used in the experiments. We rescaled or rebased the amount to reduce the likelihood of house money effects where participants in experiments tend to make riskier choices and have a higher marginal propensity to spend, e.g., (Clark, 2002). Hereafter, we only use rebased or rescaled amounts. To cover the moral issue of subjecting participants to losses in experiments, each participant received a show-up fee of K25 (USD 1.4), which is sufficient to cover the anticipated transportation costs from their homesteads.

Subsidy sessions

The subsidy sessions tested the effects of proving a targeted, time

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[4] https://www.eresconverge.com/.
[5] We rescaled the amounts to reduce the actual amounts paid in the end. These amounts are averages based on the five camps. Returns to CA were slightly higher but not significantly different as would be expected under normal rainfall conditions. The full gross margin tables are available from authors.

bound learning subsidy as an incentive for verified adoption. This was consciously framed as a conditional learning subsidy to be given to eligible farmers for a maximum of three years under the assumption that beneficiaries would have learnt enough about CA to carry on afterwards and by this time, returns from CA would be positive. This is informed by findings suggesting that positive returns from CA accrue after 2 – 5 seasons (Thierfelder et al., 2017). This is a variation from other studies that have used a once-off subsidy, e.g., Omotilewa, Ricker-Gilbert, and Ainembabazi (Omotilewa et al., 2019). The subsidy was framed as a voucher worth K3.5 for verified CA adopters.[6] This can be implemented as a top-up to the current government subsidy program or as a supplement on a smaller scale. With the subsidy, the payoff for CA was K31 under normal seasonal rainfall and K22 under below normal rainfall (Table 2). The gross margins from CA with a subsidy is higher if seasonal rainfall is normal because it is assumed that recipients would be able to buy more inputs or implements than before, which should increase productivity. The payoffs for conventional agriculture and CA without the subsidy remained unchanged. While CA with the subsidy has higher payoffs than CA without the subsidy under both normal and below normal seasonal rainfall years, some participants may choose CA without the subsidy if they have had negative experiences with the input subsidy program or any other similar programs in the past (Ngoma et al., 2018).

Seasonal rainfall forecast information sessions

This treatment tested the effects of providing timely seasonal rainfall forecast on farmers' choices of farming systems. The forecast had a 25 % chance of predicting normal seasonal rainfall given the current variability. As an added incentive for knowing the likelihood of below normal seasonal rainfall, we assumed that using CA when rainfall forecast correctly predicts below normal seasonal rainfall increases returns by 10 %. Equally, using CA or conventional agriculture when seasonal rainfall is normal increased returns by 10 %. The 10 % return used in the experiments is close to the 12 % estimated returns to information in Birthal et al. (Birthal et al., 2015). However, choosing conventional agriculture when the forecast predicted below normal seasonal rainfall attracted a 10 % 'information' penalty. For simplicity, we assumed the level of this penalty to be equal to the negative of the size of the returns to information. This session added two extra options for farmers: conventional agriculture with seasonal rainfall forecast and CA with seasonal rainfall forecast in addition to the two base options in Table 2. The payoffs for conventional agriculture and CA without seasonal rainfall forecast remained unchanged. Returns to CA with seasonal rainfall forecast and conventional agriculture with seasonal rainfall forecast were the same under normal rainfall at K30. The real benefit of CA was seen under below normal rainfall regime where returns to CA were K21 compared to *K*10 under conventional farming (Table 2). This is line with findings suggesting that CA benefits are higher under low rainfall conditions (Michler et al., 2019; Nyagumbo et al., 2020; Tesfaye et al., 2021).

Seasonal rainfall forecast and learning subsidy sessions

This treatment tested the effects of bundling seasonal rainfall forecast and a learning subsidy on farmers' choices of farming practices. As

before, this added two extra options for farmers to choose from: conventional agriculture with seasonal rainfall forecast and a subsidy, and CA with seasonal rainfall forecast and a subsidy in addition to the two base options in Table 2. The payoffs for conventional agriculture and CA without seasonal rainfall forecast remained unchanged as did returns for conventional agriculture with seasonal rainfall forecast and subsidy. This is because the subsidy only applied to CA systems and there was a 10 % penalty for using conventional agriculture when seasonal rainfall is below normal. Returns to CA with seasonal rainfall forecast and subsidy were K34 with normal rainfall and K25 with below normal rainfall (Table 2).

Empirical strategy

Because participation in the experiments was randomized, estimators such as limited probability models (LPM) or Probit can be used since the outcome variables are binary. Since every participant played every session, our data was transformed into a four-wave panel. We specified the following regression equation to assess the effects of rainfall forecasts and offering subsidies on adoption.

$$adopt_{ij} = \beta_0 + \beta_1 low\_rf_j + \beta_2 subo_j + \beta_3 normr_{t-1j} + \boldsymbol{R}_i\boldsymbol{\beta}_4 + \boldsymbol{X}_i\boldsymbol{\beta}_5 + \boldsymbol{\Omega}_i\boldsymbol{\beta}_6 + \beta_7 risk\_a_i + \beta_8 imp_i + \mu_i$$

where, $adopt_{ij}$ refers to whether participant i chose CA in experiment j, $j = 1–4$. low_rf, $subo$, and $normr_{t-1}$ are dummy variables = 1 in each case, if the forecast predicted below normal seasonal rainfall in the fourth experiment, a subsidy was offered and if the realized rainfall in the previous experiment round was normal. Our interest is to test whether either $\beta_1 > 0$ or $\beta_2 > 0$ in which case a forecast indicating below normal seasonal rainfall or offering a subsidy increased adoption of CA. $\boldsymbol{R}$ is a vector of dummy variables capturing whether a participant received seasonal rainfall forecast for the 2021/2022 season, attended a field day, and hosted a demonstration plot. $\boldsymbol{X}$ is a vector of demographics including gender, age, and education of the participant. $\boldsymbol{\Omega}$ is a measure of wealth proxied by tropical livestock units. $Risk\_and\ imp$ are dummy variables capturing whether a participant is risk averse and impatient, respectively as defined below. μ_i is an idiosyncratic error term that is independently and identically distributed (iid) with zero expected value and a constant variance $\mu_i\sim (0, \sigma^2)$.

Equation 1 was estimated using Probit and/or LPM models in Stata statistical software. Risk preferences measure individual attitudes towards risky choices, whereas time preferences measure the degree to which individuals prefer something now versus later. Following previous studies, e.g., (Dohmen et al., 2011), we measured risk and time preferences using self-reported responses to five-point Likert-Scale type questions.[7] A participant was considered risk averse if they responded, "not at all" and/or "somewhat willing" to take risks under the first question, while impatient ones are those who responded "not at all" and/or "somewhat willing" to wait to get things on the second question. The rest of the variables are defined in Table 3.

Below normal rainfall forecasts, subsidies, and hosting demonstrations are expected to increase the chance of adopting conservation agriculture, *a priori*. The effects of other variables were indeterminate ex-ante. The variables included in equation 1 are among important drivers of CA adoption and other agriculture technologies (Arslan et al., 2022; Maertens et al., 2021; Ngoma et al., 2021; Omotilewa et al.,

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[6] Government contributes K1,700 per farmer and each farmer contributes K400 in the current e-FISP. The e-FISP allows farmers to redeem a prepaid Visa card ("e-voucher") at participating agro-dealers' shops for a diverse range of inputs and implements. This contrasts with the traditional FISP which restricted farmers to mostly maize seed and fertilizers and which distributed these inputs in-kind to farmers rather than being implemented through e-vouchers redeemable at agro-dealers. The K350 (K3.5 rebased) learning subsidy proposed is 88% of the farmer contribution and would increase the total subsidy value to K2,450 from K2100. Verified adoption is certified adoption by private or public agents.

[7] **Risk preference:** How do you see yourself: are you generally a person who is willing to take risks, or do you try to avoid taking risks? (1) Not at all willing to take risks, (2) Somewhat not willing to take risks, (3) Neutral, (4) Somewhat willing to take risks, (5) Always willing to take risks. **Time preference:** How do you see yourself: are you generally a person who is impatient and wants to have 'things' now, or can you wait to get them later? (1) Not at all willing to wait to get things, (2) Somewhat not willing to wait, (3) Neutral, (4) Somewhat willing to wait, (5) Always willing to wait before I take my turn.

Table 3
Variable descriptions and summary statistics.

Variable	Description	Mean
*Outcome variables**		
CA_base	Chose CA in experiment 1 (yes = 1)	0.933
CA_subsidy	Chose CA in experiment 2 (yes = 1)	0.135
CA_and_subsidy	Chose CA and subsidy in experiment 2 (yes = 1)	0.854
CA_rainf	Chose CA in experiment 3 (yes = 1)	0.034
CA_and_rainf	Chose CA and seasonal rainfall forecast in experiment 3 (yes = 1)	0.809
CA_rainfs	Chose CA in experiment 4 (yes = 1)	0.124
CA_and_rainfs	Chose CA and seasonal rainfall forecast + subsidy in experiment 4 (yes = 1)	0.798
Independent variables		
normr_t-1	Normal seasonal rainfall in previous experiment (yes = 1)	0.517
low_rf	Below normal seasonal rainfall forecast (yes = 1)	0.674
rcvd_rain_forecast	Received seasonal rainfall forecast for 2021/2022 season (yes = 1)	0.787
attend_fday	Attended a field day in the 2021/2022 season (yes = 1)	0.157
demo_plot	Hosted a demonstration plot in the 2021/2022 season (yes = 1)	0.584
mem_coop	Member, farmer cooperative (yes = 1)	0.697
edu	Education in years	7.506
male	Male participant	0.539
age	Age in years	46.337
risk_averse	Risk averse (yes = 1)	0.135
impatient	Impatient (yes = 1)	0.112
tlu	Tropical livestock units	1.329
N		**89**

Notes: * These variables were used to define composite adoption variables used in the regressions.

2019).

We performed some robustness checks to assess potential learning and lassitude effects given a within-subject design which required each participant to play all four sessions. First, if learning effects are significant, we would expect the proportion of participants that chose a given CA option with added benefits to be higher in subsequent sessions. In this case, with learning, we would expect a larger proportion of participants to choose CA with seasonal rainfall forecast and subsidy in session 4, followed by CA with seasonal rainfall forecast in session 3, followed by CA with seasonal subsidy in session 2, and CA only in session 1. If this sequence does not hold, we can surmise that there was no significant learning effects as would be expected because the sessions had a practice round and participants were familiar with CA. Second, following Wuepper, Wree, and Ardali (Wuepper et al., 2018) and Lapierre et al. (Lapierre et al., 2023), we re-ran the models separately for game 1, 4 and, games 2 – 4 where additional information was provided on subsidies and rainfall forecast.

Results and discussion

Sample characteristics

A little over half (53 %) of the participants in the experiments were male and the majority were members of farmer cooperatives (Table 3). Participants were on average 46 years old and had completed primary education. About 11 % and 13 % were impatient and risk averse, respectively. A little over half of the participants hosted demonstration plots but only 15 % attended field days. Seasonal rainfall forecasts predicted below normal rainfall 67 % of the time in the fourth

experiment and seasonal rainfall in the previous experiment was normal about half the time.[8]

Adoption dynamics

About 93 % and 7 % of participants chose CA and conventional agriculture, respectively in the base session (Fig. 1). Introducing a learning subsidy for CA in the second session led to an 80-percentage point reduction in farmers choosing CA only when compared to the first session. In the second session, 85 % chose CA with the subsidy, 13 % still chose CA only and 1 % chose conventional agriculture. The third session with seasonal rainfall forecast saw 81 % choose CA with seasonal forecast, 3 % chose CA, 10 % chose conventional with seasonal forecast and 6 % chose conventional agriculture. About 80 % chose CA with both seasonal forecast and subsidy, 12 % CA only, 7 % CA with seasonal forecast and 1 % chose conventional in the fourth session. These results are as expected and are aligned with earlier studies indicating that subsidies improved CA adoption (Bell et al., 2016; Bell et al., 2018; Ngoma et al., 2018; Ward et al., 2018). What stands out is the fact that some farmers still chose conventional agriculture in each experiment round. This could reflect unwillingness to change where farmers stick to what they know best despite alternatives with higher returns. Such farmers may have had a bad experiences with CA or are risk averse or are not aware of the potential for CA to adapt to rainfall variability. This is similar to (Holden and Quiggin, 2017) who found that risk averse farmers in Malawi were more likely to adopt drought tolerant maize and local varieties instead of other improved varieties.

Fig. 2 is an adoption tree map that shows how farmers' choices evolved from the first to the fourth experiment session. A key result is that farmers that chose CA in the first experiment session tended to stick to choices including CA in the subsequent sessions. The majority that chose CA in the first session switched to CA with a bonus subsidy in the second session, CA with seasonal forecast in the third session and CA with seasonal forecast and subsidy in the fourth session (Fig. 2). The majority of those that chose conventional in the first session switched to CA-based choices in the subsequent sessions. These results show, albeit indirectly, that introducing a subsidy and seasonal rainfall forecast led to farmers changing their choices of farming practices (Figs. 1 and 2).

Effects of seasonal rainfall forecast and subsidies on adoption

We used the last three experiments which had treatments for regressions. As stated before, subsidies were offered in experiment sessions 2 and 4, while seasonal rainfall forecasts were provided in experiment sessions 3 and 4. Results are for models with normal seasonal rainfall (Table 4) and below normal seasonal rainfall (Table 5) in the previous 'season' or experiment round. In each table, columns 1 – 3 report Probit model results with progressively increasing covariates to check the stability of the results. The full model results are in column 3 while those in column 4 are for robustness checks and were estimated using a Generalized Linear Model (GLM) with a Probit link function.

Focusing on column 3, providing seasonal rainfall forecast predicting below normal seasonal rainfall significantly increased the probability of adoption by 8 percentage points, while offering a subsidy increased the chances of adopting CA by 11 percentage points. These results are statistically significant at 1 % level and are in line with *a priori* expectations. They are also comparable with Birthal et al. (Birthal et al., 2015) who found that information increased returns by 12 % per ha in India. Similarly, Omotilewa, Ricker-Gilbert, and Ainembabazi (Omotilewa et al., 2019) found that providing a one off subsidy increased the probability that beneficiaries would purchase hermetic bags from

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[8] We used seasonal rainfall forecast in the fourth experiment and seasonal rainfall in the third experiment since there were four rounds of experiment sessions.
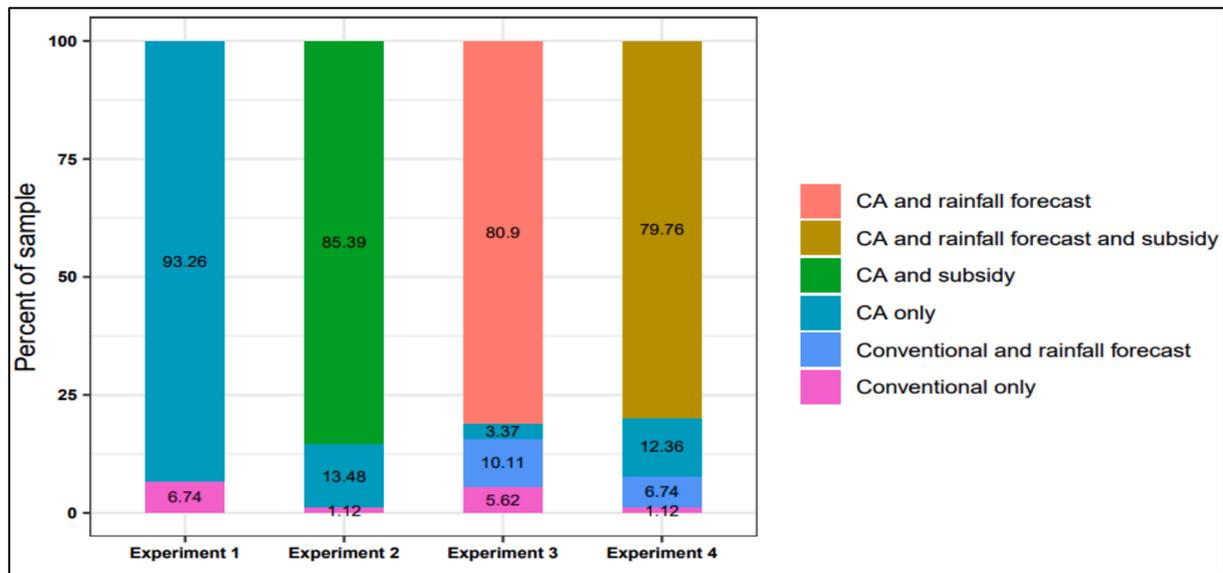
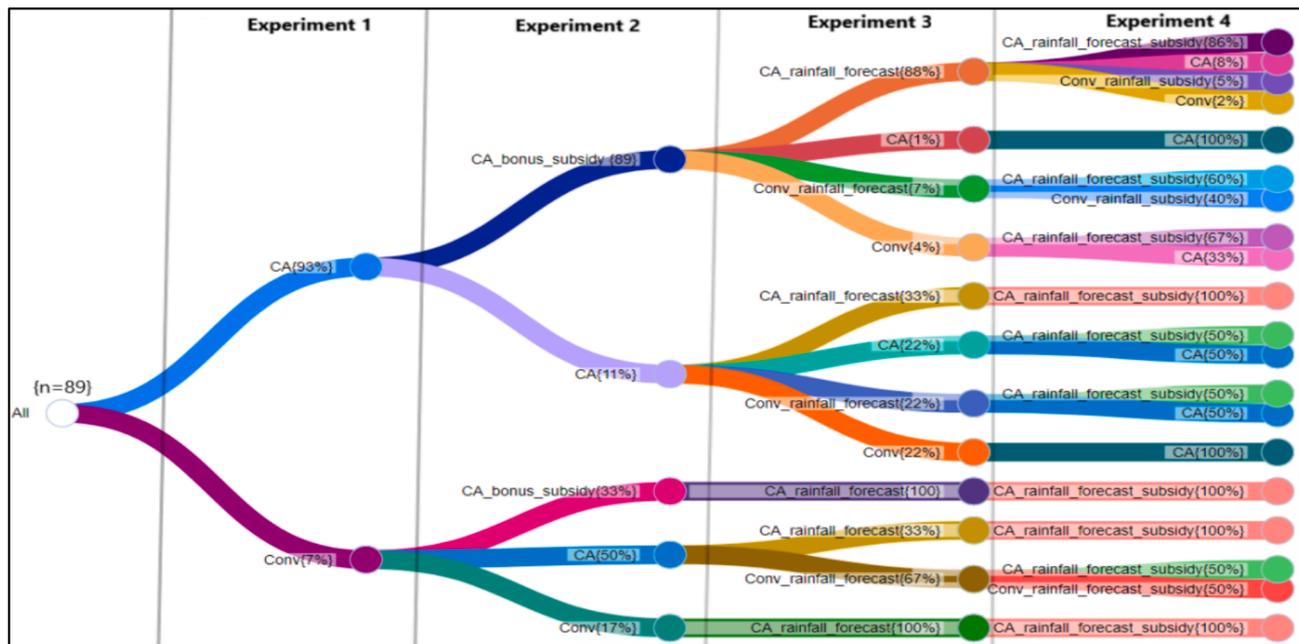**Fig. 1.** Farmer choices of different farming practices by experiment session.

Fig. 2. Changes in farmer choices of different farming practices by experiment round. Notes: CA – conservation agriculture; Conv – conventional agriculture. The added words signify the treatments. For example, CA_subsidy means CA with subsidy.

commercial sources. They are also in line with Ngoma et al. (Ngoma et al., 2018) who found that providing subsidies increased the chances of adopting CA by 12 percentage points in Zambia.

Having experienced normal seasonal rainfall in the previous experiment round was associated with 6 percentage points higher odds of adopting CA (Table 4, column 3). However, past exposure to below normal rainfall significantly reduced the probability of current CA adoption by 6 percentage points (Table 5). Results in Tables 4 and 5 are very similar. The only difference is the sign on the variable depicting normal or below normal seasonal rainfall. These results suggest that farmers did not expect two subsequent seasons to be the same, given the large rainfall variability in the region. While droughts remain the most prevalent climate shock in Zambia, it is not uncommon for both floods and droughts to occur concurrently in the same season and to alternate across years in the same area (Ngoma, Finn, and Kabisa 2024). Farmers

understand these trends and climate dynamics in Zambia (Mulenga et al., 2017), leading them to expect that normal rainfall experienced in the previous season would lead to low rainfall in the current season and vice versa. This result is related to Sesmero, Ricker-Gilbert, and Cook (Sesmero et al., 2017) who found that past exposure to poor rainfall influenced farmers to plant maize in the current season, even if there were more lucrative alternatives. As others have suggested, e.g., Foster and Rosenzweig (Foster and Rosenzweig, 2010), farmers form expectations about future outcomes based on past experiences. In terms of adoption, this suggests that farmers go through several stages before they adopt a technology. They first form expectations about returns such as yield, and then invest time and resources to learn and acquire the technology which foments their beliefs and finally, decide whether to adopt a technology (Foster and Rosenzweig, 2010; Maertens et al., 2021).
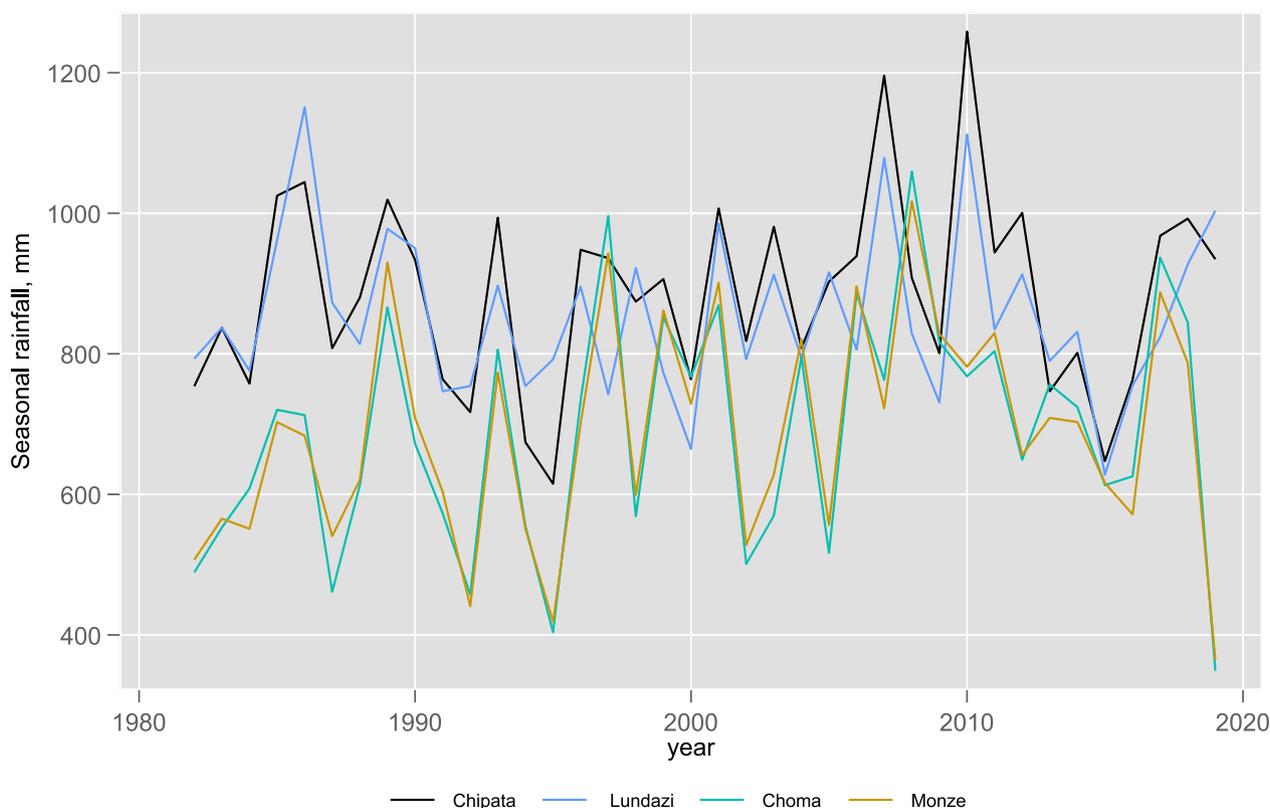
Fig. 3. Trends in seasonal rainfall in the districts where the games were played. .
Source: Authors based on data from https://www.chc.ucsb.edu/data/chirps

Table 4
Effects of seasonal rainfall forecast and subsidies on conservation agriculture adoption in experiments 2 – 4, with normal previous seasonal rainfall.

	(1)	(2)	(3)	(4)
	Model 1	Model 2	Model 3	GLM
Low rainfall forecast (yes = 1)	0.055*	0.071**	0.081***	0.081***
	(0.033)	(0.034)	(0.023)	(0.023)
Subsidy offered (yes = 1)	0.111***	0.111***	0.111***	0.111***
	(0.033)	(0.031)	(0.028)	(0.028)
Normal rainfall at *t-1* (yes = 1)	0.054**	0.068***	0.063***	0.063***
	(0.025)	(0.025)	(0.020)	(0.021)
Received forecast for 2021/22 season (yes = 1)		0.068*	0.024	0.024
		(0.041)	(0.024)	(0.024)
Attended a field day (yes = 1)		0.047	−0.005	−0.005
		(0.045)	(0.080)	(0.081)
Hosted a demo plot (yes = 1)		0.100**	0.079***	0.079***
		(0.046)	(0.023)	(0.025)
Member, farm coop (yes = 1)		−0.028	−0.044	−0.044
		(0.038)	(0.036)	(0.037)
Education, years			0.018***	0.018***
			(0.006)	(0.006)
Male participant (yes = 1)			0.016	0.016
			(0.025)	(0.026)
Age, years			0.002	0.002*
			(0.001)	(0.001)
Risk averse (yes = 1)			−0.006	−0.006
			(0.025)	(0.024)
Impatient (yes = 1)			0.034	0.034
			(0.026)	(0.026)
Tropical livestock unit			−0.010	−0.010
			(0.021)	(0.020)
Observations	267	267	267	267

Notes: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$;; models 1 – 3 estimated using random effects probit; GLM – generalized linear model.

Hosting demonstration plots increased the probability of adopting CA by 8 percentage points. This corroborates findings in Maertens, Michelson, and Nourani (Maertens et al., 2021) who found that farmers engaged in season long demonstration plots in Malawi had higher intentions to adopt. Similarly, Pangapanga-Phiri et al. (2024) found that hosting demonstration and long-term extension support were key factors for the sustained adoption of CA in Nkotakota district in Malawi. In addition Ngoma et al. (2024), found that hosting demonstrations plots speeds up the probability of adopting CA in southern Africa. An additional year of education increased the chance of adopting CA by 2 percentage points while one more year in the age of the participant is associated with 0.2 percentage points higher chances of adoption. These results are as expected. More educated farmers are more likely to better understand complex technologies like CA as do more experienced farmers, if we proxy age for farming experience, e.g.,(Ngoma et al., 2021; Tufa et al., 2023).

Effects of bundling seasonal rainfall forecasts and subsidies

There is an increasing interest in international development to test the effects of bundling innovations, under the assumption that this may lead to larger impacts. We tested the effects of bundling below normal seasonal rainfall forecast and subsidies. In theory, it is expected that bundling seasonal rainfall forecast and subsidies can augment adoption, if the two are complementary. We found that bundling seasonal rainfall forecast and subsidy did not significantly affect the probability of adopting CA practices (Table 6, column 3). We surmise from these findings that seasonal rainfall forecast, and subsidies had better influence on CA adoption singly than in combination and speculate that perhaps, they can be bundled with advisories on agronomic management, pest and disease control, and insurance, which maybe more suitable complements.

Table 5

Effects of seasonal rainfall forecast and subsidy on conservation agriculture adoption in experiments 2 – 4, with below normal previous seasonal rainfall.

	(1)	(2)	(3)	(4)
	Model 1	model 2	model 3	GLM
Low rainfall forecast (yes = 1)	0.055*	0.071**	0.081***	0.081***
	(0.033)	(0.034)	(0.023)	(0.023)
Subsidy offered (yes = 1)	0.111***	0.111***	0.111***	0.111***
	(0.033)	(0.031)	(0.028)	(0.028)
Low rainfall at $t-1$ (yes = 1)	−0.054**	−0.068***	−0.063***	−0.063***
	(0.025)	(0.025)	(0.020)	(0.021)
Received forecast for 2021/22 season (yes = 1)		0.068*	0.024	0.024
		(0.041)	(0.024)	(0.024)
Attended a field day (yes = 1)		0.047	−0.005	−0.005
		(0.045)	(0.080)	(0.081)
Hosted a demo plot (yes = 1)		0.100**	0.079***	0.079***
		(0.046)	(0.023)	(0.025)
Member, farm coop (yes = 1)		−0.028	−0.044	−0.044
		(0.038)	(0.036)	(0.037)
Education, years			0.018***	0.018***
			(0.006)	(0.006)
Male participant (yes = 1)			0.016	0.016
			(0.025)	(0.026)
Age, years			0.002	0.002*
			(0.001)	(0.001)
Risk averse (yes = 1)			−0.006	−0.006
			(0.025)	(0.024)
Impatient (yes = 1)			0.034	0.034
			(0.026)	(0.026)
Tropical livestock unit			−0.010	−0.010
			(0.021)	(0.020)
Observations	267	267	267	267

Notes: Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1; models 1 – 3 estimated using random effects probit; GLM – generalized linear model.

Robustness checks

A priori, we expected the proportion of participants who chose CA to increase with each session if there were significant learning effects. This is because introducing seasonal rainfall forecast and subsidies increased the payoffs for CA. As Fig. 4 shows, this was not the case. In fact, the proportion of participants who chose CA and complementary information packages reduced from the first to fourth session. This was expected because all participants played a practice round and were in general familiar with CA even before participating in the experiments.

The second approach for robustness checks involved re-estimating the models for all four games and for game 1, separately. Recall that the main results reported above were restricted to games 2 – 4 where additional treatments in terms of subsidy and seasonal forecast were provided. Results in Table 7 for all four games are comparable, qualitatively, to those in Table 4, suggesting no major learning effects.

Results for the first game are reported in Table 8. These are substantially different from those in Tables 4 and 7 because they are based on a smaller cross-sectional sample and include fewer variables. Having received seasonal rainfall forecast in the previous season and being male are significant drivers of farmers choosing CA. Taken together, these robustness checks do not suggest any significant learning effects, nor were there indications of lassitude among participants during field work. The fact that the session order was randomized helped to curtail any learning effects.

While there could be concerns about selection bias, this is not an issue in our case since participants in the experiments were randomly selected. We also controlled for several individual factors to allay

Table 6

Effects of bundled seasonal rainfall forecast and subsidy on conservation agriculture adoption.

	(1)	(2)	(3)
	Model 1	Model 2	Model 3
Low rainfall forecast (yes = 1)	0.105	0.114	0.143*
	(1.280)	(1.389)	(1.885)
Subsidy offered (yes = 1)	0.172**	0.172**	0.172**
	(2.367)	(2.349)	(2.322)
Below normal forecast and subsidy (yes = 1)	−0.089	−0.089	−0.089
	(−1.105)	(−1.097)	(−1.084)
Normal rainfall at $t-1$ (yes = 1)	0.047**	0.062**	0.058**
	(2.063)	(2.280)	(2.508)
Received forecast for 2021/22 season (yes = 1)		0.055	0.006
		(1.369)	(0.156)
Attended a field day (yes = 1)		0.029	−0.032
		(0.830)	(−0.597)
Hosted a demo plot (yes = 1)		0.102**	0.069*
		(2.130)	(1.891)
Member, farm coop (yes = 1)		−0.020	−0.042
		(−0.449)	(−0.935)
Education, years			0.024**
			(2.241)
Male participant (yes = 1)			0.028*
			(1.650)
Age, years			0.002**
			(2.082)
Risk averse (yes = 1)			−0.015
			(−0.322)
Impatient (yes = 1)			0.014
			(0.539)
Tropical livestock unit			−0.006
			(−0.416)
Constant	0.747***	0.640***	0.432***
	(9.818)	(7.641)	(3.960)
Observations	267	267	267
Number of hh id	89	89	89

Notes: Robust standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. All models estimated using random effects models.

concerns of any individual effects in the sessions. The unique feature of our experiments was that they were conducted alongside a detailed household survey which allowed us to match detailed farm and household level factors to the participants in the experiments.

The extent to which findings from experiments like ours are externally valid and generalizable is often questioned. Critics often point to the effects of warm glow and cognitive dissonance where participants in experiments behave differently and give socially acceptable responses. There are several facets in our experimental design to allay these fears. First, the incentives provided in experiments induced truth telling even if they do not match the high stakes in real life. This makes our experiments incentive compatible. Second, conducting experiments with farmers exposed to CA helped to minimize misunderstandings and helped farmers to quickly understand the experiment session procedures and instructions. We tested this and found a positive and statistically significant correlation between CA adoption in real life drawn from the survey, and CA adoption in the first experiment session prior to any incentives (rho = 10.10, p = 0.099). This leads to treatment validity given the close connections between options in the experiment and those in everyday lives of the participants. Framing the adoption experiments to mimic the start of the farming season when farmers chose farming practices before they know the rainfall realizations and with forecast in some sessions mirror real life experiences. And lastly, because these experiments were conducted as a subset of a larger survey, we were able to capture a lot of covariates about real life events that helped validate the tasks in experiments. For example, participants from households that hosted demonstrations in real life had higher chances of adopting CA in the experiments (Table 4). Participants in the experiments were drawn from households where CA adoption was at 12 % and use of drought
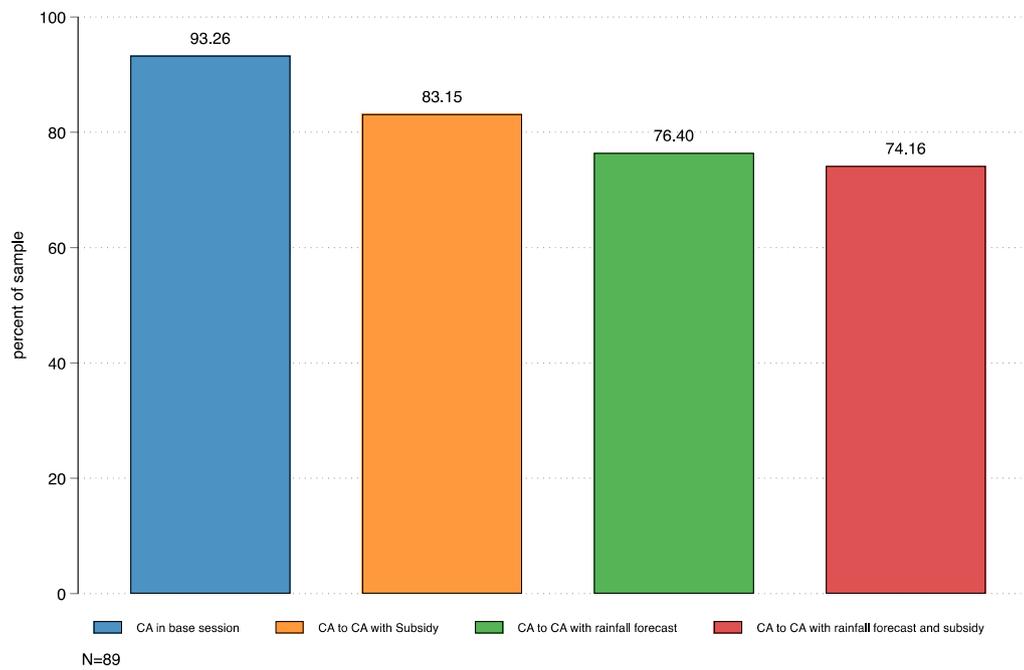
Fig. 4. Trends in proportions of participants choosing conservation agriculture (CA) in the base sessions, and CA and treatments in subsequent experiment sessions.

Table 7
Effects of seasonal rainfall forecast and subsidies on conservation agriculture adoption, all games, with normal previous seasonal rainfall.

	(1)	(2)	(3)	(4)
	Model 1	model 2	model 3	GLM
Below normal seasonal rainfall forecast (yes = 1)	0.021	0.044	0.063*	0.061*
	(0.029)	(0.038)	(0.035)	(0.034)
Subsidy offered (yes = 1)	0.067***	0.067***	0.068***	0.068***
	(0.026)	(0.025)	(0.023)	(0.023)
Below normal rainfall at *t-1* (yes = 1)	0.027	0.046	0.051	0.051*
	(0.029)	(0.037)	(0.031)	(0.030)
Received seasonal forecast for 2021/22 season (yes = 1)		0.088*	0.061*	0.059*
		(0.048)	(0.036)	(0.035)
Attended a field day (yes = 1)		0.035	−0.005	−0.003
		(0.035)	(0.067)	(0.067)
Hosted a demo plot (yes = 1)		0.072*	0.058**	0.055**
		(0.038)	(0.027)	(0.028)
Member, farm coop (yes = 1)		−0.044	−0.053	−0.053
		(0.042)	(0.037)	(0.037)
Education, years			0.013**	0.013**
			(0.005)	(0.005)
Male participant (yes = 1)			0.043*	0.044*
			(0.023)	(0.024)
Age, years			0.001	0.001
			(0.001)	(0.001)
Risk averse (yes = 1)			−0.015	−0.018
			(0.022)	(0.022)
Impatient (yes = 1)			0.044	0.044
			(0.035)	(0.035)
Tropical livestock unit			−0.020	−0.019
			(0.015)	(0.016)
Observations	356	356	356	356

Notes: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8
Drivers of CA adoption in the base games before information on seasonal rainfall forecast and subsidies.

	(1)	(2)	(3)	(4)
	Model 1	model 2	model 3	GLM
Received seasonal forecast for 2021/22 season (yes = 1)	0.115	0.114	0.142*	0.142*
	(0.085)	(0.070)	(0.083)	(0.083)
Attended a field day (yes = 1)		0.010	−0.022	−0.022
		(0.080)	(0.064)	(0.064)
Hosted a demo plot (yes = 1)		−0.070**	−0.022*	−0.022*
		(0.028)	(0.013)	(0.013)
Education, years			−0.011*	−0.011*
			(0.007)	(0.007)
Male participant (yes = 1)			0.173***	0.173***
			(0.062)	(0.062)
Age, years			−0.000	−0.000
			(0.001)	(0.001)
Risk averse (yes = 1)			−0.105	−0.105
			(0.093)	(0.093)
Tropical livestock unit			−0.037***	−0.037***
			(0.010)	(0.010)
Observations	89	89	89	89

Notes: Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; membership to farmer group and impatience dropped because of collinearity.

tolerant maize at 78 % based on the survey results. This shows *behavioral validity* where choices in real life are aligned to those in the experiments.

Despite our results demonstrating strong treatment and behavioral validity, we urge caution when generalizing the findings to the wider smallholder farmers, beyond areas where CA is common in Zambia for two main reasons. First, the economic experiments reported here were conducted in areas where farmers were very familiar with CA. As such, results may be different in places where CA is less known. Second, since the experiments were consciously designed as one-shot sessions, no learning effects are captured. This makes sense given the sample of participants, but it may be illuminating to design similar economic experiments as repeated sessions to capture learning effects to better mimic the fact that returns from CA accrue in the medium- to long-term. Future studies can be designed as randomized controlled trials to further validate the findings in this study, and to assess how such policy levers can be implemented and the enduring effects after withdrawing the policy incentives. The experimental approach used here can be used to test, ex-ante, nudges for the adoption of other agricultural technologies such as seed and fertilizer.

Conclusion

Conservation agriculture is crucial for building resilience in rainfed farming systems of southern Africa. However, adoption is not widespread. Using incentivized economic field experiments in Zambia, this paper investigated, *ex-ante*, whether providing rainfall forecasts and a time-bound learning subsidy could help increase adoption of conservation agriculture. We used a within subject design so that each of the 89 participants played all the four experiment sessions for a total of 356 observations. Participants in the experiments were randomly selected. We found that providing rainfall forecasts predicting low rainfall significantly increased the probability of adopting CA by 8 percentage points, while offering a subsidy increased the chances of adopting CA by 11 percentage points. Bundling rainfall forecasts and subsidies did not significantly influence adoption.

Having experienced normal rainfall in the previous experiment round (or 'season') was associated with 6 percentage points higher odds of adopting CA, while past exposure to low rainfall significantly reduced the probability of adoption by 6 percentage points. These results suggest that farmers did not expect two subsequent seasons to be the same given the large rainfall variability in the region. As such, normal rainfall in the last season induced farmers to expect the opposite in the current season and vice versa. This in turn dictates farmers' choices of farming practices. Other important drivers of adoption are hosting demonstration plots and education level of the participant. The findings in this paper provide evidence that providing rainfall forecasts and learning subsidies can be effective ways to understand the adoption dynamics of CA, and probably other technologies, in Zambia. These results imply a need to reframe CA as means to address low and erratic rainfall. Future studies should go a step further to assess how such policy levers can be implemented and whether these effects endure for a long time after withdrawing the subsidies. Assessing whether these can be included as part of the digital advisories, or they should be in the mainstream public extension systems is also an interesting area for future research.

CRediT authorship contribution statement

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cliser.2025.100547.

Data availability

Data will be made available on request.

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