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ANALYSIS

The role of climate and loan financing information on solar irrigation adoption among cocoa farmers in Ghana

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ABSTRACT

While climate change poses increasing risks to cocoa production, the adoption of irrigation in Ghana's cocoa sector remains low. In this context, this study examined farmers' preferences for climate and loan financing information for solar irrigation adoption. A discrete choice experiment was conducted with cocoa farmers across seven regions of Ghana. In treatment groups, we varied the availability of major season consecutive dry days information, while both groups received major season rainfall amount information, forecast spread, and financial conditions for solar irrigation adoption. The climate information projected conditions over a five-year horizon. Using mixed logit and latent class models, we found that farmers responded strongly to loan costs per month and the fraction of their farm that would be irrigated. In contrast, farmers showed limited sensitivity to climate and forecast spread information. We found that farmers were not willing to pay for rainfall amount and consecutive dry days information. We did not detect a significant difference in cocoa farmer preferences for solar irrigation when additional dry days information was provided. However, we did detect that consecutive dry days information was used during decision making. Preferences were shaped by perceptions of climate change and education levels, and not by stated attribute non-attendance. The findings highlight the importance of financial support and that transmission of climate information to farmers and actual use of this information for decision making is complex and requires a context-specific combination of climate and behavioural sciences.

1. Introduction

Climate change poses severe and growing threats to cocoa production in Ghana, with these impacts expected to intensify in the coming decades (Ariza-Salamanca et al., 2023; Obahoundje et al., 2025; Schroth et al., 2016). Altered rainfall patterns and increased temperature extremes are diminishing cocoa yields by limiting pollination, increasing pest pressures, and reducing tree health (Asitoakor et al., 2022; Carr and Lockwood, 2011; Umeh et al., 2022). The resulting low or failed cocoa yields intensify and lengthen cocoa farmers' seasonal food shortages (Chemura et al., 2020; Picot et al., 2024).

Despite the potential of irrigation to improve resilience against climate change while supporting cocoa production and improving economic stability, adoption has remained limited among farmers (Chavas and Nauges, 2020; Durga et al., 2024; Gbodji et al., 2025; Gbodji et al., 2023). This is striking given irrigated cocoa outperforms rain-fed systems in terms of yield under water-stressed conditions and that cocoa farmers show interest in solar irrigation (Adet et al., 2024; Bunn et al., 2019; Gbodji et al., 2023). High upfront investment costs and limited access to credit remain significant barriers to adaptation and especially adoption of solar irrigation technologies among sub-Saharan African farmers (Antwi-Agyei et al., 2015; Bunn et al., 2019; Durga et al., 2024). In Ghana, cocoa farmers show interest in solar irrigation but are only willing to invest below the minimum market price (Gbodji et al., 2023).

Climate information, such as climate data, forecasts, and advisory services, has the potential to support solar irrigation adoption; however, empirical findings on its realised influence remain mixed. Studies have shown that farmers rely on climate-related information to guide a range

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of operational agricultural decisions (such as determining optimal planting periods, scheduling fertiliser application, and selecting appropriate crop varieties), with limited evidence of its role in long-term farm investments (Muller et al., 2024; Nyadzi et al., 2022; Tall et al., 2018). In cocoa farming, climate information has facilitated (improved) implementation of shade trees, adjusted planting dates, and mulching practices (Maguire-Rajpaul et al., 2020). Ghanaian cocoa farmers have positively perceived climate information as a tool for enhancing their farming practices and their livelihoods, and its use has been associated with increased yields and income, and improved food security (Tham-Agyekum et al., 2024). The use of climate information was found to vary by adaptation type. Namely, climate information use was associated with the adoption of water management and multiple cropping practices among Ghanaian farmers, but showed no evidence of supporting the adoption of erosion control, pest-resistant crops, or integrated pest management (Djido et al., 2021). To date, no studies have explicitly examined the role of climate information in influencing solar irrigation adoption in the cocoa sector. Empirical studies also report that climate information is often found to be insufficiently tailored, inaccessible, or too complex for farmers to use (Baffour-Ata et al., 2022; Kosoe and Ahmed, 2022; Sarku et al., 2022; Tham-Agyekum et al., 2024).

Few empirical studies examine how climate change perceptions influence adaptation, and their results inconclusive. Climate perceptions have been found to influence stated climate information use but not influence adoption of climate change adaptation measure(s) among Ghanaian farmers (Owusu et al., 2021). Climate (risk) perceptions have been found to play a key role in the adoption of agricultural technologies (Ahmed et al., 2022; Ndamani and Watanabe, 2016). Socio-demographic variables have been more widely shown to influence farmer adaptation (Antwi-Agyei et al., 2015; Dang et al., 2019).

To address this research gap, we examine Ghanaian cocoa farmers' preferences for climate information, financing conditions, and irrigation coverage in decisions to adopt solar irrigation. We explored this using a discrete choice experiment (DCE), as it is a suitable method for analysing decision-making under realistic yet hypothetical scenarios, namely choices that closely resemble the actual trade-offs that farmers face in solar irrigation adoption (Mariel et al., 2021; Train, 2009). We also investigate how climate change perceptions, socio-demographic characteristics, and stated information attendance shape these preferences. We quantified the relative preferences of climate forecasts and financing terms in the decision to adopt solar irrigation. To assess the influence of additional climate information, we implemented two treatment groups, where in one treatment group the choices included only rainfall information, and the other was provided rainfall and consecutive dry days information.

Our study is additionally novel for examining the interlinkages between climate information, financing, and the adoption of a specific adaptation, namely, solar irrigation. Previous DCE studies have typically considered these factors in isolation. For example, studies have assessed farmers' preferences for climate information, but few have linked this information to the adoption of specific climate adaptation measures (Hounnou et al., 2023; Lechthaler and Vinogradova, 2017; Molina-Maturano et al., 2022; Tesfaye et al., 2023; Tesfaye et al., 2019; Wens et al., 2021). Additionally, loan financing was either not included (Hounnou et al., 2023; Lechthaler and Vinogradova, 2017; Molina-Maturano et al., 2022; Tesfaye et al., 2023) or included in a limited binary way (access or no access to credit) (Tesfaye et al., 2019). Wens et al. (2021) included accessibility of credit schemes as well as credit rate. Although forecast accuracy has been considered in some DCEs, to our knowledge, none have evaluated preferences for forecast spread. Hounnou et al. (2023) and Wens et al. (2021) assessed forecast accuracy in binary terms (accurate vs. inaccurate), while Lechthaler and Vinogradova (2017) studied accuracy as varying percentages of correct information. Other DCEs have not included climate information, instead examining preferences for adaptation support more broadly (Schrieks et al., 2025; Wassie et al., 2024) or focusing on particular adaptation practices, such as irrigation (solar, motor, or rope-and-wash) and credit access (Balasubramanya et al., 2023).

2. Methods

2.1. Description of study area

We surveyed farmers in seven main cocoa-producing regions of Ghana (see Fig. 1) (Akpoti et al., 2023). Although no national farmer registry exists, Bymolt et al. (2018) estimated there to be 800,000 farmers across these main regions. Cocoa-growing communities were identified through expert-guided purposive sampling in collaboration with regional COCOBOD officers. We recruited farmers with awareness of or experience with irrigation to ensure informed survey responses. Fifteen enumerators collected data in June 2024 from twelve villages across seven regions. The sample contains a total of 578 adult respondents from Ashanti (93), Brong Ahafo (45), Central (98), Eastern (93), Volta (53), Western (95), and Western North (101) regions, with region sample sizes reflecting each region's share of the national cocoa production. Respondents from different regions were evenly distributed between climate information treatment groups.

The agro-ecological zones in these areas are predominantly semi-deciduous forest, but also include rainforest, coastal savannah, and a transitional zone (Gbetibouo et al., 2017). The major rainy season (March to July) is critical for cocoa pod development and avoiding disease outbreaks, which are influenced by rainfall amount and consecutive dry days (Gbetibouo et al., 2017; Läderach et al., 2013; Medina and Laliberte, 2017; Schroth et al., 2016). During the major rainy season, mean annual rainfall ranges from 800 to 2800 mm, depending on the specific agro-ecological zone (Gbetibouo et al., 2017). Annual temperature in Ghana varies between 21 and 32 degrees Celsius (Obahoundje et al., 2025). To date, adaptation strategies among cocoa farmers have largely focused on shade management, improved cocoa varieties, crop changes and diversification, and income diversification to cope with climate risks (Amfo and Ali, 2020; Asante et al., 2017; Denkyirah et al., 2017; Kosoe and Ahmed, 2022).

2.2. Choice experiment, survey design, and implementation

To inform the design of the DCE, we conducted focus groups and survey pre-tests among respondents within the seven cocoa-growing regions. A total of twelve focus group discussions were held in twelve different communities, providing valuable insights into the livelihoods, challenges, and climate change resilience strategies of cocoa farming households. Participants reported challenges such as droughts causing reduced water availability and crop failure. Additionally, pests and diseases, such as black pod disease and capsid bugs, negatively impacted yields. In response to these stresses, communities adopted several adaptive strategies, such as spraying crops to combat pests, frequent farm visits to manage risks, and engaging with extension officers for technical support. Farmers indicated interest in crop diversification and the adoption of irrigation systems to mitigate water scarcity. They also expressed a clear need for relevant climate indicators to manage these disruptions, with major season rainfall amounts and consecutive dry days emerging as meaningful metrics directly linked to their climate-related challenges. Table 1 presents the final selection of attributes for the DCE.

We also conducted a survey pre-test with 63 respondents. The KoboToolbox software (Kobo, 2025) was used to implement the pre-test and final survey. Ethical approval was granted by the International Water Management Institute Internal Review Board, and informed consent was obtained from all participants.

Costs per unit of SIP reflected realistic prices for solar irrigation systems based on focus groups and Gbodji et al. (2023). The finance period and annual interest rates in the DCE mirrored typical loan durations and development-oriented rates (5–22%) at the time of fieldwork

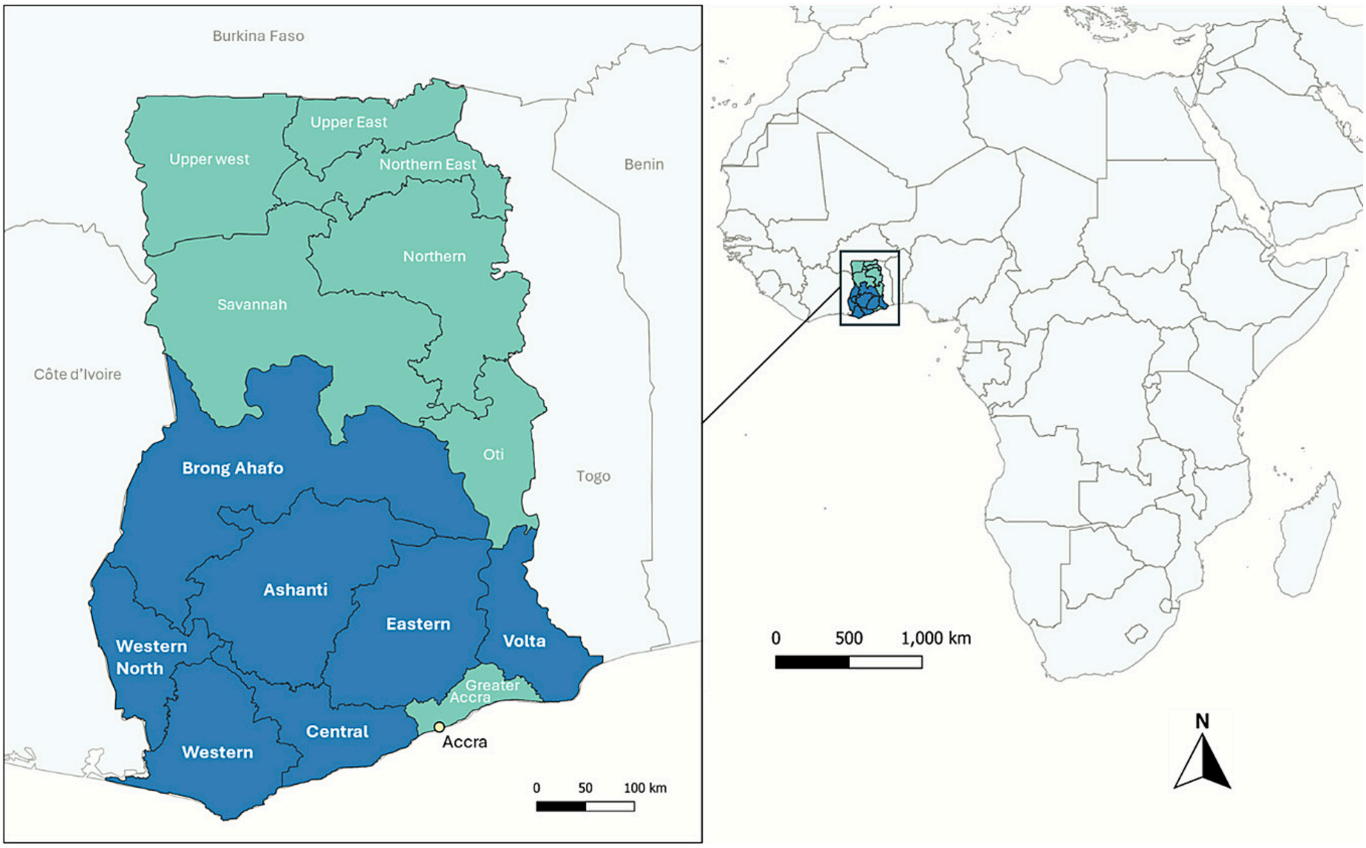

Fig. 1. Map of Ghana showing seven study regions (dark blue) (QGIS.org, 2025).

Table 1
Overview of attributes and levels used in the choice experiment.

Attribute	Explanation	Units	Levels
Major season rainfall	Rainfall amount prediction during the major season over the next five years.	Millimetres (mm)	650; 700; 750; 800; 850
Major season consecutive dry days	Number of consecutive days with precipitation below 1 mm, during the major season over the next five years.	Number of days	3; 4; 5; 6; 7
Forecast spread	Spread in the rainfall forecast.	Millimetres (mm)	50; 100; 150
	Spread in consecutive dry days forecast.	Number of days	1; 2; 3
Fraction of farm with SIP	Farm area to be covered by solar irrigation farming.	Percentage	25; 50; 75; 100
Costs per unit of SIP	Cost per unit area for solar irrigation farming.	Ghanaian cedi (GH₵)	60,000; 100,000; 140,000
Finance period	Payback period in years, at 20% interest.	Years	1; 2; 4; 6

Note: SIP refers to solar irrigation pumps.

(Bank of Ghana, 2025). The monthly loan payments (ranging from GH₵ 1437 to GH₵ 12,969, based on the cost and payback period attributes) and total loan payments (ranging from GH₵ 66,696 to GH₵ 241,416) were listed on each of the choice cards and were calculated using constant payments and a constant annual interest rate.[1]

The climate information was based on the latest Ghana climate report, with a status quo climate of 800 mm of rainfall, 6 consecutive dry days, and a forecast spread range of +150 and − 200 mm for rainfall, and + 1 and − 2 consecutive dry days (Obahoundje et al., 2025). In the statistical analyses, major season rainfall amount, forecast spread, fraction of farms with solar irrigation, and loan cost were scaled by 1/100; thus, these estimated MMNL and LC-MNL model coefficients should be interpreted per 100 units.

Two treatment groups were considered to test our hypotheses. Group one received major season rainfall information, whereas group two also received the number of consecutive dry days as a choice attribute. An example of a choice card for treatment group two is shown in Fig. 2, with the additional number of dry days attribute (see Appendix A).[2]

We generated a D-efficient experimental design in MATLAB. Six blocks were included, with each respondent completing six choice tasks. The only non-zero attribute priors used were those for the fraction of farm with solar irrigation (3.5) and finance period (0.6), which were

[1] Monthly payment = (present value * periodic interest rate) / [1 - (1 + periodic interest rate)^(− total number of interest periods)], where periodic interest rate = annual percentage rate / number of interest periods per year. Total payments = monthly payment * total number of interest periods.

[2] Reference information availability also varied within each treatment group, but this is not examined further in this paper.

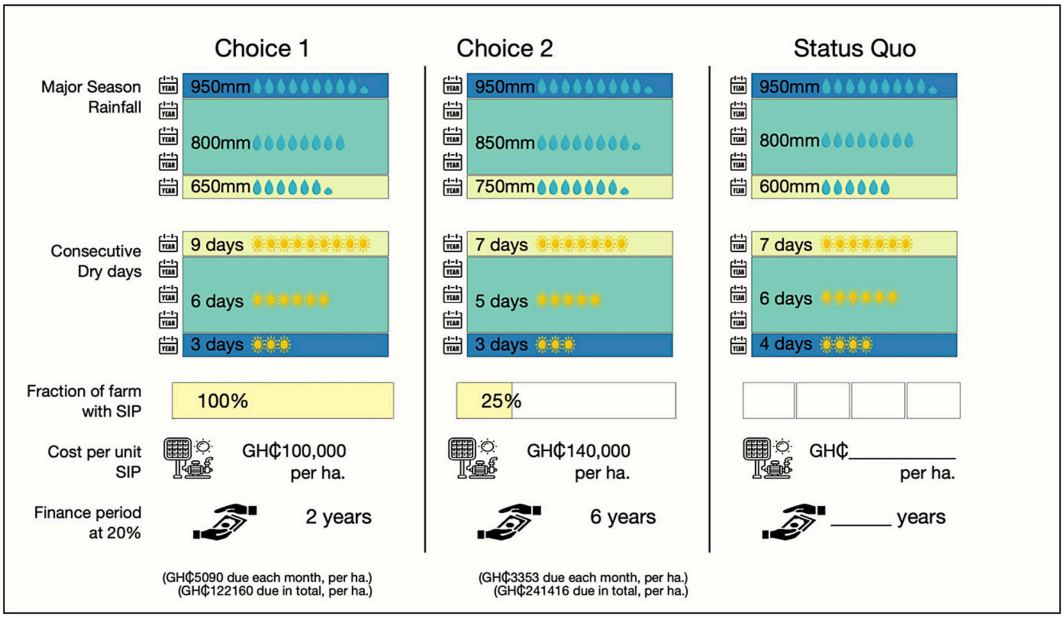

Fig. 2. Choice card for treatment group two, with two climate indicators.

based on our pilot results.

The survey comprised multiple sections. First, we asked about respondents' household and livelihood information, including demographics informed by prior studies (Akrofi-Atitianti et al., 2018; Gbodji et al., 2023; Yiridomoh et al., 2022). This included irrigation practices to establish the respondent-specific status quo. This was followed by adaptation behaviour questions, based on protection motivation theory (PMT) (Attiogbé et al., 2024; Rogers, 1983; Rogers, 1975; Schrieks et al., 2025; Wens et al., 2021). The DCE section included an example choice card and four comprehension checks, followed by an assessment of attribute non-attendance (ANA) (Lew and Whitehead, 2020). Climate perceptions were measured using a five-point single-item scale from van Valkengoed et al. (2021), and with questions about sources of climate information use. The survey concluded with questions about water use.

A total of 634 respondents completed the survey, although 56 were excluded due to missing responses on climate change perceptions questions, failure to pass DCE comprehension checks, or identification as protest bidders (see Appendix A). We analysed the data using the package 'Apollo' (version 0.3.4) in software R (version 4.4.2) (Hess and Palma, 2019; R Core Team, 2024).

2.3. Hypotheses and econometric framework

2.3.1. Hypotheses

The potential of climate information as a driver of solar irrigation adoption, combined with the role of financing conditions, remain underexplored. This study thus investigates the following two hypotheses:

H1. Rainfall amount and consecutive dry days information influences the decision to adopt solar irrigation.

H2. Preferences for solar irrigation differ when both rainfall amount and consecutive dry days information are provided, compared to when only rainfall amount information is provided.

We test H1 using mixed multinomial logit (MMNL) and latent class models (LCM) (see sections 2.3.2 and 2.3.3) to analyse the preferences for DCE attributes, while allowing for heterogeneity. H2 builds on H1 by assessing whether individuals' preferences for solar irrigation differ when both rainfall and consecutive dry days information are provided, compared to when only rainfall data is presented. This will be tested by comparing estimated willingness to pay (WTP) between treatment groups from both MMNL and LCM (see Section 2.4). We furthermore consider whether climate perceptions, socio-demographics, and ANA influence DCE choices (see Appendix C).

2.3.2. Mixed logit model

The MMNL model is grounded in the Random Utility Model in which individuals are assumed to select the alternative that provides the highest utility (McFadden, 1974). The MMNL model extends the standard multinomial logit (MNL) model by allowing model coefficients to vary randomly across individuals (Hensher and Greene, 2003; McFadden and Train, 2000; Train, 2009).

The utility U_{njt} that individual $n \in \{1, 2, .., N\}$ derives of choosing alternative $j \in \{1, 2, .., J\}$ in choice situation $t \in \{1, 2, .., T\}$ is specified as:

$$U_{njt} = \beta_n' X_{njt} + \varepsilon_{njt}, \tag{1}$$

Where X_{njt} is a vector of the observed attributes describing alternative j, and β_n is an unobserved individual-specific vector of preference parameters. Alternative i_{nt} is chosen by individual n at choice situation t if and only if $\forall j \neq i_{nt}, U_{ni_{nt}t} > U_{njt}$. The random term ε_{njt} is assumed to be independently and identically distributed (iid) extreme value type I across alternatives, individuals, and choice situations. The random coefficients β_n are treated as draws from a specified distribution $f(\beta)$, selected to capture preference heterogeneity (Mariel et al., 2021).

Conditional on a given draw of β_n, the probability that individual n chooses a sequence of alternatives $i = \{i_{n1}, \ldots, i_{nT}\}$ across T choice tasks is the product of standard logit probabilities:

$$L_{ni}(\beta) = \prod_{t=1}^{T} \left[\frac{e^{\beta_n' X_{ni_{nt}t}}}{\sum_{j=1}^{J} e^{\beta_n' X_{njt}}} \right], \tag{2}$$

with an unconditional probability of $P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta$ as ε_{njt} is independent across choice tasks. Since this integral has no closed-form solution, simulation-based methods are used to estimate the mean and covariance parameters (Train, 2009). We estimated MMNL models with and without correlated random parameters. Allowing for correlated random parameters relaxes the diagonal constraint on the variance–covariance matrix (Mariel et al., 2025; Mariel and Meyerhoff, 2018; Scarpa and Alberini, 2005).

2.3.3. Latent class model

To further explore unobserved sources of heterogeneity and identify segments of respondents with distinct preference structures, we additionally estimated a latent class multinomial logit (LC-MNL) model (Boxall and Adamowicz, 2002; Greene and Hensher, 2003). Instead of modelling continuous variation in preferences across individuals (as in MMNL), the LC-MNL model assumes that the population is composed of a finite number of latent (unobserved) classes, each characterized by its own class-specific utility parameters. In this framework, the utility that individual n derives from choosing alternative j in choice situation t, conditional on class membership $q \in \{1, \dots, Q\}$, is specified as:

$$U_{njt|q} = \beta_q' X_{njt} + \varepsilon_{njt}, \tag{3}$$

where β_q is a class-specific vector of preference parameters, and ε_{njt} remains an iid extreme value type I error term. Given membership in class q, the probability that individual n chooses alternative i_{nt} in choice situation t is:

$$P_{nt}\ (i_{nt}|q) = \frac{e^{\beta_q' X_{ni_{nt}t}}}{\sum_{j=1}^{J} e^{\beta_q' X_{njt}}}, \tag{4}$$

Conditional on class membership, the probability of observing a sequence of choices $i = \{i_1, \dots, i_T\}$ is computed analogously to the standard logit model:

$$L_{ni|q} = \prod_{t=1}^{T} [P_{nt}(i_{nt}|q)] = \prod_{t=1}^{T} \left[\frac{e^{\beta_q' X_{ni_{nt}t}}}{\sum_{j=1}^{J} e^{\beta_q' X_{njt}}} \right], \tag{5}$$

In addition to identifying segments with distinct preference structures, we estimated a LC membership model to examine whether sociodemographic, attitudinal and perception characteristics influence the probability of belonging to a given class. The probability that an individual n belongs to class q, denoted H_{nq}, can be specified using a multinomial logit (MNL) function based on individual-specific covariates Z_n:

$$H_{nq} = \frac{e^{\gamma_q' Z_n}}{\sum_{r=1}^{Q} e^{\gamma_q' Z_{nr}}}, \tag{6}$$

With normalization $\gamma_Q = 0$ for identification. If no covariates are included, Z_n consists only of a constant (delta), and H_{nq} reduces to fixed class probabilities. The unconditional probability of individual n making a sequence of choices, weighted by the probability of belonging to each class is:

$$P_{ni} = \sum_{q=1}^{Q} H_{nq}\, L_{ni|q}, \tag{7}$$

The full sample log-likelihood is the sum over all individuals:

$$\log L = \sum_{n=1}^{N} \log(P_{ni}), \tag{8}$$

This formulation enables the identification of discrete segments in the population, with internally homogeneous but between-class heterogeneous preferences.

2.3.4. Willingness to pay

In MMNL and LC-MNL models, the scale parameter is normalised to one and absolute coefficient estimates cannot be directly compared across models (Train, 2009). Ratios of coefficients, such as WTP, remain comparable across models, as the scale effects cancel out in these ratios (Swait and Louviere, 1993). We base our model comparisons on WTP values, which reflect the trade-off respondents are willing to make between a given attribute and cost.

The WTP for different attributes is calculated as:

$$WTP = -\left(\frac{\beta_k}{\beta_{\text{Loancost}}}\right), \tag{9}$$

where β_k is the coefficient of the attribute k, and $\beta_{Loancost}$ is the monetary or loan cost coefficient. This represents the additional cost a respondent is willing to incur for a one-unit increase in each attribute. We calculated WTP estimates using the Krinsky and Robb, 1990, Krinsky and Robb, 1986 method as this performs as well as other approaches in estimating confidence intervals, and does not assume that WTP is symmetrically distributed (Hole, 2007). We report median values, as they are robust to extreme values (Bliemer and Rose, 2013), and tested for differences in WTP between models by examining confidence interval overlap and applying the Poe et al. (2005) test for statistical differences between WTP distributions.

2.4. Model specification

2.4.1. Mixed logit model

We specified two MMNL models to analyse the DCE choices. The MMNL model was specified as follows:

$$U_{njt} = \alpha_j{*}ASC + \beta_1{*}RAIN_{jt} + \beta_2{*}SPREAD_{jt} + \beta_3{*}FRAC_{jt} + \beta_4{*}LOANCOST_{jt} + \beta_5{*}DRY_{jt} + \varepsilon_{njt}, \tag{10}$$

where the term α_j is the intercept, applied through an alternative-specific constant (ASC), which takes the value one for the status quo and zero for the hypothetical irrigation alternatives. The variable $RAIN_j$ represents the mean amount of rainfall during the major season, with the associated coefficient β_1. β_2 captures the effect of rainfall (and consecutive dry days) forecast spread ($SPREAD_j$). β_3 corresponds to the fraction of land that can be irrigated ($FRAC_j$). The monthly loan cost of irrigation per hectare ($LOANCOST_j$) is represented by β_4 (under an annual interest rate of 20%). Only in treatment two, we estimated β_5 as this represents the coefficient for the mean number of consecutive dry days in the major season (DRY_j). In this specification, we included a single attribute monthly loan costs, rather than costs per unit of SIP and loan payback period separately. We do this because monthly loan costs were also stated to respondents on the choice cards, and better capture choices about monthly cost carrying capacity. This specification also improves the model's ability to detect respondent preferences by leveraging twelve attribute levels (rather than three cost levels, and four payback period levels separately). A limitation of this approach is that total costs of solar irrigation and payback durations can no longer be disentangled. In our specification, all attribute coefficients were assumed to follow a normal distribution, $\beta \sim N(b, W)$, where we estimate the mean b and covariance of W. The cost attribute, however, was specified to follow a lognormal distribution, $\ln\beta \sim N(b, W)$, to ensure that the marginal utility of cost remains negative, in line with common practice (Mariel et al., 2021). We used 20,000 Sobol draws to estimate these distributions (Czajkowski and Budziński, 2019).

2.4.2. Latent class model

To explore if we can identify discrete groups, we estimated the following LC-MNL model:

$$U_{njt|q} = \alpha_j^q{*}ASC + \beta_1^q{*}RAIN_{jt} + \beta_2^q{*}SPREAD_{jt} + \beta_3^q{*}FRAC_{jt} + \beta_4^q{*}LOANCOST_{jt} + \beta_5^q{*}DRY_{jt} + \varepsilon_{njt}, \tag{11}$$

where q indexes latent classes, and α_j^q and β_k^q are class-specific. We determined the optimal number of classes using model fit criteria (e.g., AIC, BIC). We estimated β_5^q only in treatment group two, where respondents received additional consecutive dry days information. We included class membership, and assessed whether classes were influenced by education level, climate change beliefs and ANA.

3. Results

3.1. Socio-demographic statistics

Table 2 shows the descriptive statistics of the 578 cocoa farmers in our sample. The age of respondents varied between 22 and 87 years, with an average of 54 years. According to the Ghana Statistical Service (2021), the average rural household size in Ghana in 2021 is 4, which is smaller than the average in our sample (mean = 5.39). Women comprise 51% of the rural population, which is higher than in our sample (39%). Most respondents (53%) have completed junior secondary/middle-level education, followed by those with no formal education (16%), primary education (16%), senior secondary/high school education (9%), and higher education (5%). There were no statistical differences between the two treatment groups across demographic variables; however, we found differences across regions consistent with Ghana Statistical Service (2021)'s population census (see Appendix B).

Cocoa production was the primary livelihood for 93% of respondents in our sample, followed by food crop production (2%). Most respondents were self-employed in agriculture (86% without employees; 8% with employees). According to PMT, adaptive behaviour is shaped by perceived adaptation efficacy, self-efficacy in implementing the adaptation, and adaptation costs (Rogers, 1983; Rogers, 1975). Although only 3% of respondents had (solar) irrigation, they perceived solar irrigation as equally effective as other adaptation strategies (crop diversification, pruning and shade management, fertiliser and pesticide application, income diversifying activities). In line with PMT, we found that respondents reported lower perceived ability to implement solar irrigation and considered it the costliest option compared to crop diversification, pruning and shade management, fertiliser and pesticide application, off-farm work and diversification. The main barrier(s) to implementing any type of irrigation were high cost (77% of respondents), lack of availability of solar irrigation (21%), and lack of knowledge (30%).

3.2. Climate information and climate change perceptions

Most respondents accessed weather information primarily through radio (90%), with fewer relying on neighbours or friends (27%) or the internet (7%). The majority accessed weather information daily (56%) or weekly (27%). Climate change-related information was also accessed frequently, daily by 46% and weekly by 26%. Climate change-related information influenced farm management decisions, either substantially (45%) or to some extent (42%).

We found that most respondents (strongly) agreed that climate change is real and anthropogenic and that it will affect them negatively (Table 3). They also (strongly) agreed with statements that climate change will affect their area and that its impacts will take a short time to manifest. On average, respondents expressed a weak agreement with the predictability of climate change. These beliefs did not differ across treatment groups (see Appendix B).

Respondents' climate change perceptions were reflected in their observations of recent weather patterns. On average, they reported a moderate decline in rainfall during the major season over the past five years (mean = −0.70, s.d. = 1.10), along with an increase in the number of consecutive dry days (mean = 0.80, s.d. = 1.22), which is in line with previous studies and past recorded weather changes (Fosu-Mensah et al., 2012; Obahoundje et al., 2025). Expectations for rainfall over the next five years were on average neutral (mean = −0.02, s.d. = 1.13), although a slight increase in consecutive dry days was anticipated (mean = 0.32, s.d. = 1.14).

3.3. Attribute (non-)attendance

Asking which attribute(s) respondents considered most important, the majority reported the fraction of land irrigated (38%), the loan financing period (29%), or costs (17%). Only 9% of the respondents ranked rainfall during the major season as most important, and only 6% ranked the number of consecutive dry days as the most important attribute. However, the climate attributes mattered for choices, as only 9% of the respondents stated that they had ignored the rainfall and/or dry days attributes in their choices. Most respondents (70%) stated that they did not ignore any of the attributes, and the cost per unit of SIP attribute was most often mentioned as ignored (by 11% of the respondents).

3.4. Mixed logit model results

Table 4 presents the MMNL model (Eq. (10)) for the two treatment groups separately. We report the MMNL model without accounting for correlation because accounting for correlation between random parameters did not significantly improve model fit and parameter estimates differed only marginally (See Appendix C).

We did not detect that major season rainfall information significantly affected cocoa farmer choices in either treatment, unlike the consecutive dry days information. Farmers in treatment group two preferred to

Table 2
Sample descriptive statistics of socio-demographic variables ($n = 578$).

Characteristics	Description	Mean (s.d.)	min, max
Age	Age of the respondent, in years	53.86 (12.20)	22, 87
Gender	Gender of the respondent (1 = female, 0 = male)	0.39 (0.49)	0, 1
Household size	Number of individuals in the respondent's household	5.43 (2.57)	1, 17
Irrigation system	If the respondent has installed irrigation on their farm (1 = yes, 0 = no)	0.03 (0.17)	0, 1
Land ownership	Land area owned, in hectares (ha)	4.69 (5.26)	0, 60.73
Number of productive cocoa trees	Number of cocoa trees in full production	3693 (7526)	0, 100000

Note: Standard deviations (s.d.) are presented in brackets. There are no significant differences between treatment groups in these socio-demographics (see Appendix B).

Table 3
Survey results for climate change perceptions.

Climate change perception scale (*abbreviation used in LC-MNL* Table 6)	Mean (s.d.)
I believe that climate change is real (*Reality*)	3.67 (0.57)
The main causes of climate change are human activities (*Causes*)	3.18 (0.97)
I believe we can predict how the weather will change (*Predict*)	2.63 (0.82)
Climate change will bring about serious negative consequences (*Valence*)	3.51 (0.59)
My local area will be influenced by climate change (*Spatial distribution*)	3.35 (0.64)
I believe the weather in my area will change (*Area weather*)	2.99 (0.71)
It will be a short time before the consequences of climate change are felt (*Temporal distribution*)	3.07 (0.86)

Notes: Respondents (n = 578) rated their agreement on a 4-point scale (1 = strongly disagree to 4 = strongly agree), reformulated here for clarity. The original questions included in our survey are in line with van Valkengoed et al. (2021). Standard deviations (s.d.) are presented in brackets.

Table 4
Choice experiment results of mixed logit models.

Attributes	Treatment group one: Rainfall information[a]			Treatment group two: Rainfall and dry day information[a]			Difference WTP
	Mean estimate (s.e.)	St. Dev. estimate (s.e.)	Median WTP - GH₵ per month[b] [95% CI]	Mean estimate (s.e.)	St. Dev. estimate (s.e.)	Median WTP - GH₵ per month[b] [95% CI]	Poe et al. (2005) *p*-value[c]
ASC	−9.160 *** (2.329)	9.012 *** (1.968)		−12.609 *** (2.666)	9.906 *** (2.055)		
Rainfall	0.055 (0.058)	0.092 (0.121)		−0.085 (0.053)	0.057 (0.102)		
Forecast spread	0.213 * (0.105)	0.377 (0.309)	7.61 [−1.31, 17.79]	0.187 * (0.091)	0.000 (0.024)	7.43 [−1.27, 14.93]	0.4772
Dry days	N/A	N/A	N/A	0.077 ** (0.029)	0.007 (0.015)	306.04 [−265.85, 1035.58]	
Fraction irrigated	3.497 *** (0.342)	2.574 *** (0.358)	127.69 [78.70, 204.47]	3.623 *** (0.294)	2.354 *** (0.360)	144.93 [108.13, 194.41]	0.3293
Loan cost (log) per month	−3.604 *** (0.133)	0.690 *** (0.339)		−3.692 *** (0.135)	0.729 *** (0.198)		
Model summary statistics							
No. individuals	280			298			
No. observations	1680			1788			
AIC	2246.44			2310.02			
BIC	2300.71			2375.89			
Log-likelihood	−1113.22			−1143.01			

[a] Rob. s.e. and rob. t-ratio denote robust standard errors and t-statistics, respectively. CI refers to 95% confidence intervals. The models were estimated using 20,000 Sobol draws. Two-sided significance is indicated with asterisks: *** = $p<0.001$, **= $p<0.01$, *=$p<0.05$. Rainfall, forecast spread, irrigated fraction, and loan cost were scaled by 1/100; coefficients are interpreted per 100 units. The loan cost coefficient is log transformed, ln(coefficient) and normally distributed with mean and variance m s and hence a comparable mean is $\exp(m+s/2)$, variance is $\exp(2m+s)\,[\exp(s)-1]$ (Train, 2009). All other coefficients are assumed to be normally distributed.
[b] WTP is calculated using the Krinsky and Robb (1990, 1986) method with 20,000 draws.
[c] One-sided significance is indicated with asterisks: *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$.

Table 5
Results of the latent class model with underlying multinomial logit model (LC-MNL).

Attributes	Treatment group one: Rainfall information [a]				Treatment group two: Rainfall and dry day information[a]			
	Class A		Class B		Class A		Class B	
	Estimate (Rob. s.e.)	Rob. t-ratio	Estimate (Rob. s.e.)	Rob. t-ratio	Estimate (Rob. s.e.)	Rob. t-ratio	Estimate (Rob. s.e.)	Rob. t-ratio
ASC	−1.936 *** (0.498)	−3.888	1.987 (2.577)	0.771	−2.833 *** (0.514)	−5.511	2.611 (2.798)	0.933
Rainfall mean (in hundreds)	0.075 (0.051)	1.481	−0.268 (0.300)	−0.893	−0.053 (0.048)	−1.104	−0.088 (0.301)	−0.292
Forecast spread (in hundreds)	0.136 (0.09)	1.501	0.637 (0.660)	0.965	0.157 (0.083)	1.906	−0.074 (0.365)	−0.204
Dry days mean	N/A	N/A	N/A	N/A	0.076 ** (0.025)	2.968	0.029 (0.113)	0.26
Fraction irrigated (in hundreds)	2.695 *** (0.224)	12.023	2.280 ** (0.830)	2.746	3.032 *** (0.228)	13.309	0.966 (1.609)	0.6
Loan costs (in hundreds) per month	−0.024 *** (0.002)	−11.068	−0.032 * (0.015)	−2.155	−0.025 *** (0.002)	−10.313	0.004 (0.007)	0.587
Class membership model								
Constant (delta)	2.24 *** (0.204)	10.964	0 (N/A)	N/A	2.512 *** (0.241)	10.407	0 (N/A)	N/A
Class allocation								
Mean probability	0.904		0.096		0.925		0.075	
Model summary statistics								
Number of individuals	280				298			
Number of observations	1680				1788			
Log-likelihood	−1147.40				−1177.76			
AIC	2316.80				2381.51			
BIC	2376.49				2452.87			

[a] Rob. s.e. and rob. t-ratio denote robust standard errors and t-statistics, respectively. Two-sided significance is indicated with asterisks: *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$. Rainfall, forecast spread, irrigated fraction, and loan cost were scaled by 1/100; coefficients are interpreted per 100 units.

adopt solar irrigation when the number of consecutive dry days was higher, as reflected in the positive and significant corresponding coefficient. In treatment group two, the forecast spread significantly affected preferences for solar irrigation; the higher the forecast spread, the greater the preference for solar irrigation. In treatment group one, the coefficient of the forecast spread attribute was significant; however, this effect disappeared when accounting for correlated parameters (see Appendix C).

The proportion of irrigated land and the financial attributes influenced decision-making in both treatment groups. The significant and positive coefficient for fraction irrigated indicates a preference for larger proportions of land to be irrigated with solar irrigation. In both treatment groups, we found significant heterogeneity in preferences for the fraction of land to be irrigated, as reflected in the significant corresponding standard deviation. Finally, the cost attribute, measured as the log of monthly loan payments, was significant and negative in both treatments, with significant heterogeneity. As theoretically expected, respondents preferred lower monthly loan costs, reinforcing the sensitivity of respondents to loan financing conditions. The influence of costs and fraction of irrigated land on decision-making is consistent with the respondent stated rankings from Section 3.3.

The ASC estimate was significant and negative in both treatments, indicating preferences for the adoption of solar irrigation compared to the status quo. The significant standard deviation of the ASC in both treatment groups indicated significant heterogeneity between respondents' in their preferences for solar irrigation adoption.

3.5. *Latent class model results*

In the LC-MNL model (Eq. (11)), we identified two latent classes (see Table 5). In both treatment groups, over 90% of respondents had a high probability of belonging to one class, suggesting that respondents shared relatively homogeneous preferences.

The LC model results for the choice attributes were consistent with those of the MMNL model. In class A for both treatment groups, we found that farmers preferred adopting solar irrigation over the status quo (significant negative ASC coefficient), more land to be irrigated with solar pumps (significant positive fraction coefficient), and lower monthly loan costs (significant negative loan cost coefficient). In treatment group two class A, we found that the coefficient for consecutive dry days information was significant and positive (as in the MMNL model).

In treatment group one, we found significant coefficients for class B. The fraction irrigated and loan cost coefficients were significant for both classes. In class B, farmers were more cost sensitive, and less driven by preferences for the fraction of land irrigated compared to class A. In treatment group two, no significant effects for any attributes were found for class B, indicating that the preferences of 7% of the respondents are inconclusive.

Table 6
Results of the latent class model including class membership model with underlying multinomial logit model (LC-MNL).

Attributes	Treatment group one: Rainfall information[a]				Treatment group two: Rainfall and dry day information[a]			
	Class A		Class B		Class A		Class B	
	Estimate (Rob. s.e.)	Rob. t-ratio	Estimate (Rob. s.e.)	Rob. t-ratio	Estimate (Rob. s.e.)	Rob. t-ratio	Estimate (Rob. s.e.)	Rob. t-ratio
ASC	−1.944 *** (0.503)	−3.866	2.084 (2.512)	0.829	−2.793 *** (0.533)	−5.239	2.362 (2.959)	0.789
Rainfall mean (in hundreds)	0.075 (0.051)	1.482	−0.254 (0.295)	−0.859	−0.053 (0.048)	−1.097	−0.124 (0.330)	−0.375
Forecast spread (in hundreds)	0.135 (0.090)	1.495	0.681 (0.667)	1.021	0.156 (0.082)	1.898	−0.031 (0.438)	−0.070
Dry days mean	N/A	N/A	N/A	N/A	0.076 ** (0.026)	2.967	0.011 (0.134)	0.084
Fraction irrigated (in hundreds)	2.692 *** (0.225)	11.984	2.347 ** (0.847)	2.77	3.026 *** (0.231)	13.110	0.989 (1.728)	0.573
Loan costs (in hundreds) per month	−0.024 *** (0.002)	−11.017	−0.034 * (0.016)	−2.097	−0.024 *** (0.002)	−10.128	0.004 (0.009)	0.447
Class membership model								
Constant (delta)	1.963 (1.630)	−1.205	0 (N/A)	N/A	0.246 (0.764)	1.322	0 (N/A)	N/A
Below median education	−1.030 * (0.436)	−2.364	0 (N/A)	N/A	−0.855 (0.474)	−1.802	0 (N/A)	N/A
Reality climate change (*Reality*)[b]	0.851 * (0.361)	−2.355	0 (N/A)	N/A	0.614 * (0.250)	−2.458	0 (N/A)	N/A
Predictability future climate (*Predict*)[b]	0.706 * (0.360)	1.965	0 (N/A)	N/A	0.837 * (0.386)	2.170	0 (N/A)	N/A
Stated ignored costs	−0.710 (0.554)	−1.280	0 (N/A)	N/A	−0.606 (0.630)	−0.962	0 (N/A)	N/A
Class allocation								
Mean probability	0.903		0.097		0.926		0.074	
Model summary statistics								
Number of individuals:	280				298			
Number of observations:	1680				1788			
Log-likelihood:	−1137.23				−1169.35			
AIC:	2304.46				2372.70			
BIC:	2385.86				2466.01			

[a] Rob. s.e. and rob. t-ratio denote robust standard errors and t-statistics, respectively. Two-sided significance is indicated with asterisks: *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$. Rainfall, forecast spread, irrigated fraction, and loan cost were scaled by 1/100; coefficients are interpreted per 100 units.

[b] Belief variables are measured on a four-point scale from strongly disagree (=1), until strongly agree (=4). Full questions and summary statistics are shown in Table 3.

We included a class membership component to explore which individual characteristics influence assignment to either class (Table 6). In both treatment groups, two variables significantly influenced class membership: perceived reality of climate change (*Reality*), and the perceived ability to predict future weather conditions (*Predict*). Additionally, whether education is below average level (*Below median education*) was a significant predictor of class membership in treatment group one. ANA to costs, however, was not significant in either treatment group. The climate change belief variables are endogenous to the model, and as such, the direction of all class membership variable effects should not be interpreted; only their role in influencing latent class allocation should be acknowledged (Alcorta and Mariel, 2025). The core model results of the LC-MNL model with class membership remained robust and interpretable. These findings suggested that climate change perceptions and beliefs, beyond demographic characteristics, may influence preferences for adaptation measures. We further found that climate change beliefs significantly influenced the preference to select the status quo across all choice tasks (see Appendix C).

3.6. Willingness to pay

In the MMNL model, we found that respondents who saw one climate indicator in their choice cards (treatment group one) were willing to pay for a larger fraction of irrigated land. Their WTP was estimated at GH₵ 128 per irrigated hectare per month to increase the fraction of land irrigated by 1%. For the total farm area to be completely irrigated, this would equate to GH₵ 12,800 per month per hectare. For a mean-sized farm (4.69 ha, see Table 2), this would equate to GH₵ 60,032 for the farm to be fully solar irrigated, with a confidence interval ranging between GH₵ 36,910 and GH₵ 95,896. In treatment group two, respondents were willing to pay GH₵ 145 per irrigated hectare per month to increase the fraction of land irrigated by 1%. Accordingly, for a mean-sized farm, the mean WTP to fully irrigate a cocoa farm was estimated at GH₵ 68,005 per month, ranging between GH₵ 50,713 and GH₵ 91,178.

The LC-MNL model results corresponded to lower WTP values for irrigated land than the MMNL model (see Table 7). In treatment group one, across both classes, we find that farmers' WTP increased as a larger fraction of their land was irrigated, as the confidence intervals for the corresponding attribute exclude zero. The WTP for a mean-sized farm with fully implemented solar irrigation for class A is GH₵ 51,979 (ranging from GH₵ 42,050 to GH₵ 64,356) and for class B is GH₵ 32,352 (ranging from GH₵ 14,511 to GH₵ 64,689). The WTP of farmers in class A increased more strongly as a larger proportion of their land would be irrigated than in class B. However, the overlapping confidence intervals between the two classes suggest that these differences are not statistically significant. In treatment group two, farmers in class A showed an estimated WTP closer to that identified in the MMNL model; for a mean-sized farm with fully implemented solar irrigation the WTP is GH₵ 57,884, ranging from GH₵ 46,984 to GH₵ 71,804.

Table 7
Willingness to pay estimates from of the latent class model including class membership model with underlying multinomial logit model (LC-MNL).

Attributes[a]	Treatment group one: Rainfall information		Treatment group two: Rainfall and dry day information[a]	
	Class A	Class B	Class A	Class B
	WTP - GH₵ per month[b] [95% CI]	WTP - GH₵ per month[b] [95% CI]	WTP - GH₵ per month[b] [95% CI]	WTP - GH₵ per month[b] [95% CI]
Dry days mean	N/A	N/A	309.51 [130.02, 503.33]	
Fraction irrigated	110.83 [89.66, 137.22]	68.98 [30.94, 137.93]	123.42 [100.18, 153.10]	

[a] We omitted WTP for rainfall amount, and forecast spread, as these coefficients were not significant in the LC-MNL model (Table 6). This also applies to WTP values in treatment group two, class B.
[b] WTP is calculated using the Krinsky and Robb (1990, 1986) method with 20,000 draws.

These monthly WTP estimates for a fully solar irrigated farm suggest that one-year loans for solar irrigation would require subsidies to be viable, while multi-year loan monthly costs would align with WTP. The monthly per-hectare payments required for a one-year loan at the current market price of a solar irrigation system exceed our corresponding estimates of farmers' WTP from all models (and classes). To encourage uptake of a one-year loan, monthly subsidies would have to range from GH₵ 3,571 to GH₵ 11,166 per hectare (see Appendix D). In contrast, the monthly payments associated with a current multi-year loan fall below our WTP estimates for all models, except for treatment group one LC-MNL Class B, which would still require a subsidy of GH₵ 3,027 per hectare per month. However, when we account for the confidence intervals around our WTP estimates, it becomes less clear whether WTP is above or below market prices.

The WTP values found for consecutive dry days in the MMNL model (GH₵ 306 for solar irrigation for each additional forecasted consecutive dry day) and the LC-MNL model class A (GH₵ 310) are comparable, although their WTP confidence intervals are not. In contrast to the MMNL model, the LC-MNL model WTP confidence intervals for information about consecutive dry days exclude zero. As the LC-MNL captures heterogeneity discretely, it identifies homogeneous classes and produces narrower confidence intervals than the MMNL model. Including class-membership covariates in the LC-MNL additionally support the identification of homogeneous classes. This difference in WTP confidence intervals suggests that a specific subgroup of farmers are WTP for consecutive dry days, but that this preference is not consistent across our full sample to produce significant WTP values in the MMNL model.

Using the MMNL model results, we compared the WTP and their confidence intervals to evaluate whether including two climate indicators changed preferences for solar irrigation adoption compared to a single indicator. While the mean WTP values show some variation in magnitude, the confidence intervals for all variables overlap substantially, suggesting no statistically meaningful differences. This is supported by the Poe et al. (2005) test results (Table 4, rightmost column). Taken together, these findings suggested that the inclusion of two climate indicators, compared to only one, did not have a significant effect on WTP for solar irrigation.

4. Discussion

4.1. Do cocoa farmers use climate information?

In our tests of H1, we found that consecutive dry days information was used during decision-making, whereas rainfall information was not. The use of forecast spread information was minor and significance was inconsistent across models. In the context of adopting solar irrigation, forecast spread did not appear to play a large role in influencing adaptation decisions for cocoa farmers. This is consistent with the use of other forms of forecast uncertainty communication; for instance, Nyamekye et al. (2021) found that the use of probabilistic forecasts with longer lead times did not influence adaptation measure adoption among Ghanaian rice farmers. The influence of consecutive dry days information was significant but limited compared to the strong effect of financing attributes.

To address H2, we compared WTP across treatments and found no evidence that providing additional major season consecutive dry days information significantly changed solar irrigation adoption preferences. It is plausible that the range of climate information levels was not sufficiently wide to elicit a significant effect among our participants. Our attribute range was limited to minimise the risk of misinformation; we intentionally based our climate information levels for rainfall, consecutive dry days, and forecast spread on the most recent and credible climate change projections for Ghana (Obahoundje et al., 2025).

Our results could suggest that the amount of major season rainfall was not relevant to farmers in deciding whether to adopt solar irrigation. Climate services limited to information about rainfall and temperature may not be comprehensive enough to support farmer adaptation decision-making (Kosoe and Ahmed, 2022). An extensive review by Singh et al. (2018) suggests that climate information was relevant for users for short-term decisions based on daily, weekly, or seasonal climate information, unlike our multi-year climate attributes. Alternatively, farmers may have found information on rainfall distribution, such as the occurrence of prolonged dry or wet spells, more relevant for decision-making than total rainfall amounts. We deemed it unlikely that respondents did not use the rainfall information due to a lack of understanding. While complexity in information is a known challenge between climate information providers and cocoa farmers (Baffour-Ata et al., 2022; Kosoe and Ahmed, 2022), we conducted a pretest and focus groups to identify well-understood and impactful climate indicators, consistent with existing literature (Djido et al., 2021; Maguire-Rajpaul et al., 2020; Tham-Agyekum et al., 2024). Our survey included comprehension checks, and enumerator clarification was provided as needed. We excluded 12 respondents who did not understand the experiment, reducing the likelihood that our findings reflect misunderstanding.

4.2. Are cocoa farmers willing to pay for climate information?

While consecutive dry days influenced decision-making, the estimated WTP confidence intervals included zero (in the MMNL model), indicating no conclusive evidence that farmers are willing to pay more for solar irrigation under such forecasts. Forecasted rainfall amounts and forecast spread had no significant effect on preferences, in line with findings of Antwi-Agyei et al. (2021). This may be due to our sample size being relatively small for a two-treatment group experimental design, which may have reduced statistical power and the robustness of subgroup analyses (Mariel et al., 2021). On the other hand, Tesfaye et al. (2023) found that farmers in Rwanda were willing to pay for accurate climate information, alongside market price information. However, their DCE did not provide the climate information in combination with an adaptation option; respondents might be generally willing to pay for climate information, but when it is tied to a specific adaptation strategy, their needs may become more specific. Our results may reflect a low ability to pay or WTP by Ghanaian cocoa farmers more generally, as found in Asare and Kofituo (2023).

4.3. What is the role of financial loan conditions in solar irrigation adoption?

Our results suggest that farmers were more concerned about the financial conditions for solar irrigation than about the climate information provided. One reason for this may be financial insecurity; Wongnaa and Babu (2020) found that few cocoa farmers in Western and Brong-Ahafo Regions of Ghana had access to credit and hence struggled to afford climate change adaptation. Access to credit was a significant predictor of whether farmers adopted climate change adaptation strategies in Attiogbé et al. (2024). Gbodji et al. (2023) demonstrated that diversified farm-income alongside access to off-farm activity influenced farmers' willingness to invest in solar irrigation. Cocoa farmers also expressed low confidence in the usefulness of climate information for supporting farm investment decisions (Tham-Agyekum et al., 2024).

Participating farmers in our study were willing to pay for more of their land to be irrigated with solar irrigation. This could reflect Ghanaian farmers' perceived trust in, and recognition of, the potential benefits of solar irrigation for improving cocoa cultivation. Our findings show that perceived adaptation efficacy of solar irrigation was comparable to more commonly adopted strategies. Similar perceptions of solar irrigation's benefits for cocoa cultivation have been identified in previous studies (Adet et al., 2024; Bunn et al., 2019; Gbodji et al., 2023). Respondents perceived solar irrigation as costly and reported lower self-efficacy in implementing it, which may explain its limited uptake relative to other adaptation strategies.

4.4. Do climate change beliefs influence solar irrigation adoption?

Our results indicate that climate change beliefs significantly affect class membership and shape the likelihood of choosing the status quo without solar irrigation. Beliefs in the reality of climate change and predictability of weather influenced latent class allocation (see LC-MNL Table 6), and reduced the likelihood of selecting the status quo without solar irrigation (see Appendix C). These findings align with Dang et al. (2019), who emphasised the role of cognitive and psychological factors in farmers' adaptation decisions. Protest responses are unlikely to explain these patterns, as we excluded respondents who consistently chose the status quo alternative, ignored attributes, and cited protest motives (see Appendix A) (Meyerhoff and Liebe, 2010; Meyerhoff and Liebe, 2006).

5. Conclusion

This study examined cocoa farmers' preferences for climate and financing information in supporting climate adaptation through the adoption of solar irrigation, their willingness to pay for such information, and the role of climate change perceptions in shaping these preferences, research gaps identified in Madhuri (2023) and Muller et al. (2024). We explored this using a DCE conducted with cocoa farmers across the seven main cocoa-producing regions of Ghana. The DCE focused on two major adoption barriers to solar irrigation: financing and climate information. Respondents were randomly assigned to treatment groups that received either major season rainfall forecasts alone or rainfall combined with consecutive dry days forecasts.

Our results suggest that climate information alone is likely insufficient to support the adoption of solar irrigation among cocoa farmers in Ghana. While most farmers preferred solar irrigation to the status quo, decisions were primarily influenced by loan payments and irrigation coverage; farmers favoured lower monthly payments and greater area irrigated. Farmers were willing to pay for a multi-year solar irrigation loan, but not for a one-year loan, as the associated monthly payments were substantially higher, even if short-term loans have lower total repayment costs. Financial assistance would be required to support the uptake of one-year loans.

Although we did not find that major season rainfall information was used in decision-making, major season consecutive dry days had a significant impact on preferences for solar irrigation adoption; solar irrigation was preferred when more major season consecutive dry days were forecast for the coming five years. When significant, forecast spread had a limited influence compared to financing information.

Cocoa farmers in Ghana believed that the climate is changing and that climate change is a reality, although belief in the ability to predict weather changes varied. Both these beliefs influenced preferences to adopt solar irrigation. In the LC-MNL model, climate change beliefs significantly influenced class allocation in both treatment groups.

Overall, our results emphasise the need for financing mechanisms tailored to farmers' constraints and local, context-specific climate information, while considering climate change beliefs. Further research is needed to explore alternative climate metrics that may hold greater relevance for cocoa farmers' adaptation decisions. Additionally, further investigation into the design of financing mechanisms, such as variations in interest rates, repayment schedules, or financing models, could provide valuable support to all stakeholders along the chocolate value-chain, as climate change adaptation will be needed to secure a steady cocoa-supply. Understanding how these financial preferences differ across farmer profiles may offer more targeted support for scaling up the adoption of solar irrigation in the cocoa sector.

CRediT authorship contribution statement

Lotte C.F.E. Muller: Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation. **Andrew R. Bell:** Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Marie-Charlotte Buisson:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **Carlos Calvo-Hernandez:** Writing – review & editing, Resources, Methodology, Investigation, Conceptualization. **Kekeli Gbodji:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Salomon Obahoundje:** Writing – review & editing, Resources, Investigation. **Giulia Zane:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Marije Schaafsma:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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. Choice experiment design

A.1. Treatment groups

In our DCE, we have 5 different sets (blocks) of 6 choice cards per respondent. Per treatment group, each respondent was randomly assigned into choice card versions (Table A.1).

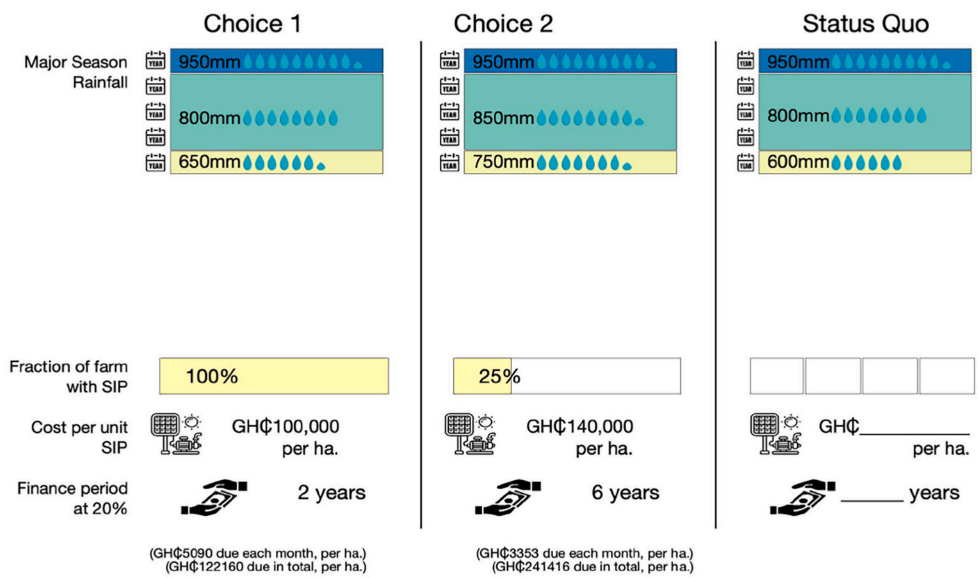
Table A.1
Number of respondents per treatment group, allocated to choice task versions (blocks).

Choice card versions	Treatment group one: Rainfall information	Treatment group two: Rainfall and dry day information	Total
1	68	65	133
2	70	61	131
3	56	71	127
4	47	61	108
5	39	40	79
Total	280	298	578

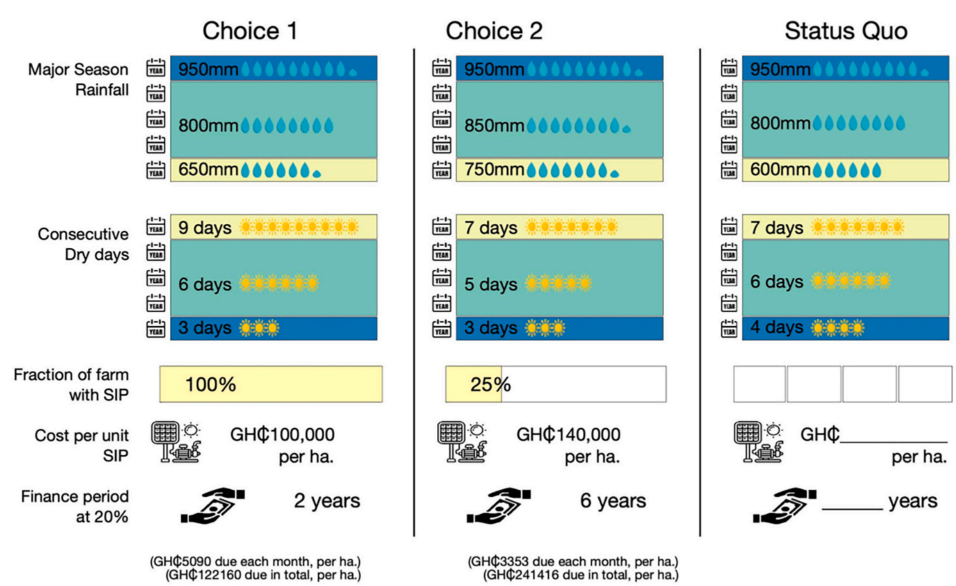
We developed two survey versions across two treatment groups (Table A.2.). Each group used identical choice card designs (same attribute values) but varied in the inclusion of information on consecutive dry days during the major.

Table A.2
Overview of different treatments in the DCE and example choice cards.

Treatment group one: One climate indicator
Major season rainfall



Treatment group two: Two climate indicators
Major season rainfall and consecutive dry days



A.2. Data selection

Table A.3
Data selection process highlighting removed observations.

Reason observations removed	No. observations removed	Remaining observations
Respondent listed infinite fraction of land irrigated.	2	632
Respondents' existing loan payback period is listed as longer than 100 years.	1	631
Respondents with missing values in the climate change perceptions.	18	613
Respondents did not pass the DCE comprehension check after the enumerator provided additional explanation.	12	601
Protest bids. Respondents were classified as protestors if they met all the following criteria:	23	578

1. They selected the status quo option in all six choice tasks; AND
2. They reported ignoring at least one attribute during the DCE; AND
3. The stated reason(s) for ignoring the attribute(s) was deemed a protest. We considered the following reasons a protest:
   a. *I don't believe that rainfall/temperature will change.*

(*continued on next page*)

Table A.3 (*continued*)

Reason observations removed	No. observations removed	Remaining observations
b. *I don't believe we can predict how rainfall or drought will change.*		
c. *I don't believe the costs are as indicated on the cards, I make my own cost calculations.*		
d. *I don't believe I can obtain such a loan anyway.*		
FINAL SAMPLE	56	578

Appendix B. Test of sub-sample differences

B.1. Additional descriptive statistics

Table B.1
Wilcoxon test results of differences in socio-demographic statistics across treatment groups.

Variable	Mean (s.d.)		Wilcoxon Test statistic	p-value
	Treatment group one: rainfall	Treatment group two: rainfall & drydays		
Age in years	53.26 (12.22)	54.43 (12.18)	39553	0.280
Gender (female)	0.4 (0.49)	0.38 (0.49)	42299	0.733
Gender household head (female)	0.29 (0.46)	0.27 (0.44)	42878	0.458
Household size in number of people	5.2 (2.32)	5.65 (2.78)	37937	0.058
Irrigation implemented	0.02 (0.13)	0.04 (0.2)	40785	0.112
Land ownership (hectares)	3577.49 (7678.53)	3801.29 (7390.12)	40893	0.680
No. of productive cocoa trees	480.76 (1105.55)	708.86 (2316.76)	39035	0.165

Note: n = 578, where treatment group one has a sample size of 280, and treatment group two a sample size of 298.

Table B.2
Test results of differences in socio-demographic statistics across regions.

Variable	Region	
	F-statistic	Regions pairwise sig. diff. (p<0.05)
Age in years	3.291 **	Western-Ashanti
Gender of the respondent (female)	3.349 **	Central-Brong Ahafo/ Western North-Brong Ahafo/ Western North-Western
Gender of the household head (female)	2.442 *	Central-Brong Ahafo/ Western North-Brong Ahafo/
Household size in number of people	2.760 *	Western-Eastern/ Western North-Eastern
Irrigation implemented	2.552 *	Eastern-Ashanti/ Volta-Ashanti / Western-Ashanti
Land ownership (hectares)	8.264 ***	Brong Ahafo-Ashanti/ Central-Brong Ahafo/ Eastern-Brong Ahafo/ Volta-Brong Ahafo/ Western-Brong Ahafo/ Western North-Central/ Western North-Volta/ Western North-Western
No. of productive cocoa trees	4.145 ***	Brong Ahafo-Ashanti/ Central-Brong Ahafo/ Eastern-Brong Ahafo/ Volta-Brong Ahafo

Note: Statistical significance is indicated with asterisks, where *** = $p<0.001$, **= $p<0.01$, *=$p<0.05$

Differences between regions (in Table B.2) in household size, gender and age are reflected in the Ghana census (Ghana Statistical Service, 2021).

Table B.3
Wilcoxon test results of differences in stated attribute non-attendance across treatment groups.

Attribute ignored	Mean (s.d.)		Wilcoxon Test statistic	p-value
	Treatment group one	Treatment group two		
Rainfall amount	0.08 (0.27)	0.1 (0.3)	40798	0.354
Consecutive dry days	0.08 (0.27)	0.11 (0.31)	40378	0.188
Fraction of farm irrigated	0.07 (0.25)	0.09 (0.29)	40631	0.252
Irrigation cost	0.1 (0.31)	0.11 (0.31)	41421	0.781
Financing payback period	0.07 (0.26)	0.08 (0.28)	41349	0.694
Other	0.03 (0.17)	0.01 (0.08)	42632	0.044
None of the above	0.72 (0.45)	0.66 (0.47)	44089	0.141

Note: n = 578, with treatment group one n_1 = 280, treatment group two n_2 = 298.

B.2. Climate change perceptions

After the DCE, we asked respondents about their perceptions of climate change (see Table B.5). We find no significant differences between treatment groups in respondents' climate change perceptions.

Table B.4
Wilcoxon test results of differences in climate change perceptions across treatment groups.

Climate change perceptions statements	Mean (s.d.)		Wilcoxon Test statistic	p-value
	Treatment group one	Treatment group two		
I believe that climate change is real	3.69 (0.53)	3.65 (0.6)	42592	0.585
The main causes of climate change are human activities	3.21 (0.94)	3.15 (1.01)	42327	0.744
I believe we can predict how the weather will change	2.61 (0.84)	2.65 (0.80)	40808	0.628
Climate change will bring about serious negative consequences	3.50 (0.59)	3.51 (0.65)	41308	0.814
My local area will be influenced by climate change	3.33 (0.63)	3.37 (0.28)	39880	0.302
I believe the weather in my area will change	3.01 (0.69)	2.98 (0.72)	42887	0.496
It will be a short time before the consequences of climate change are felt	3.06 (0.87)	3.08 (0.85)	41256	0.806

Note: n = 578, with treatment group one n_1 = 280, treatment group two n_2 = 298. Climate change perception questions are from the scale developed by an van Valkengoed et al. (2021), and have been recoded into the same direction; respondents rated their agreement on a 4-point scale (1= strongly disagree, to 4 = strongly agree).

In Table B.5 we find that women on average are less confident that we can predict how the weather will change compared to male cocoa farmers.

Table B.5
Wilcoxon test results of differences in climate change perceptions across gender.

Climate change perceptions statements	Mean (s.d.)		Wilcoxon Test statistic	p-value
	Male	Female		
I believe that climate change is real	3.69 (0.54)	3.63 (0.6)	41428	0.271
The main causes of climate change are human activities	3.21 (0.97)	3.13 (0.99)	41517	0.319
I believe we can predict how the weather will change	2.69 (0.78)	2.54 (0.87)	43580	0.035
Climate change will bring about serious negative consequences	3.53 (0.56)	3.47 (0.62)	41441	0.312
My local area will be influenced by climate change	3.38 (0.61)	3.31 (0.68)	41189	0.396
I believe the weather in my area will change	2.99 (0.73)	2.99 (0.66)	40418	0.673
It will be a short time before the consequences of climate change are felt	3.10 (0.85)	3.03 (0.88)	41343	0.38

Note: n = 578, with 353 male and 225 female respondents. Climate change perception questions are from the scale developed by an van Valkengoed et al. (2021), and have been recoded into the same direction; respondents rated their agreement on a 4-point scale (1= strongly disagree, to 4 = strongly agree).

References Appendix B

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Appendix C. Additional results

C.1. Analysis of status quo choices

Although the MMNL and LC-MNL show that the majority of respondents prefer solar irrigation adoption, there were 35 respondents (6% of the sample) who consistently chose the status quo in all shown choice cards. Namely, 20 respondents in treatment group one, and 15 respondents in treatment group two (35 in total). These respondents who prefer the status quo are from Ashanti (4 respondents, 4.3% out of total in Ashanti), Brong Ahafo (2 respondents, 4.4%), Central (2 respondents, 2.0%), Eastern (6 respondents, 6.5%), Western (17 respondents, 17.9%) and Western North (4 respondents, 4.0%) regions. We find none of the respondents in the Volta region with these preferences.

We investigate the role of climate perceptions, socio-demographics, and attribute non-attendance (ANA) on status quo preferences across all six choice tasks using logistic regression, with strict status quo preference as the dependent variable.

To investigate the determinants of status quo (SQ) preferences across all choice tasks, we estimate a logistic regression model as follows:

$$\begin{aligned} SQ_n &= \beta_0 + \beta_1 {}^*Reality_n + \beta_2 {}^*Predict_n + \beta_3 {}^*Causes_n + \beta_4 {}^*ANAcost_n \\ &+ \beta_5 {}^*Media_n + \beta_6 {}^*Female_n + \beta_7 {}^*Age_n + \beta_8 {}^*Householdsize_n + \beta_9 {}^*Trees_n \\ &+ \beta_{10} {}^*Otherwork_n + \beta_{11} {}^*Fertpest_n + \varepsilon_n \# \end{aligned} \tag{3}$$

Where SQ_n is a binary variable indicating whether respondent n chose the status quo in all six DCE tasks. The independent variables capture perceptions of climate change (Reality, Predict, Causes), self-reported ANA of cost, media influence, and socio-demographic and livelihood characteristics.

Table C.1
Results logistic regression on status quo selection (n = 578).

Dependent variable: Always status quo (=1)	Estimate (S.E.)	z value	Odds ratio	95% confidence interval
Intercept	6.704 *** (2.009)	3.337	815.515	[17.395, 47897]
Age in years	-0.007 (0.016)	-0.444	0.993	[0.963, 1.025]
Gender (female)	0.423 (0.435)	0.972	1.526	[0.653, 3.639]
Household size in number of people	-0.137 (0.083)	-1.642	0.872	[0.735, 1.020]
Number of productive cocoa trees (in hundreds)	0.001 (0.002)	0.449	1.001	[0.996, 1.004]
Adaptation: other work	-0.785 (0.416)	-1.886	0.456	[0.199, 1.027]
Adaptation: fertiliser & pesticides	-1.306 * (0.653)	-1.999	0.271	[0.079, 1.057]
Stated ignored costs	0.701 (0.557)	1.257	2.015	[0.639, 5.807]
Climate change information use[a]	-1.052 *** (0.268)	-3.93	0.349	[0.203, 0.584]
Belief: Reality climate change (*Reality*)[b,c]	-0.741 * (0.331)	-2.239	0.477	[0.250, 0.925]
Belief: Predictability future climate (*Predict*)[b]	-1.208 *** (0.297)	-4.067	0.299	[0.162, 0.521]
Belief: Human causes of climate change (*Causes*)[b]	0.449 (0.246)	1.828	1.567	[0.994, 2.628]
Model Statistics				
No. Observations/ individuals	578			
AIC	217.418			
Log-likelihood	-96.709			

[a] Climate change information use ranges from none (1), very little (2), some (3), or a lot (4).
[b] Belief variables are measured on a scale of strongly disagree (1), to strongly agree (4). Full questions are shown in Table 3 of the main paper text.
[c] The highest forecast spread inflation factors (VIF) was for the variable *reality* with value 1.28, indicating low multicollinearity (see Table C.2 for full VIF table).

From the logistic regression results (Table C.1), we find that attitudes toward climate information significantly affect the decision whether to invest in solar irrigation. Specifically, individuals who reported that climate-related information does not influence their farm decisions showed a higher tendency to prefer the status quo. Similarly, those who did not believe that weather patterns can be predicted, or who rejected the reality of climate change, were also more inclined to choose the status quo and did not express to be willing to invest in solar irrigation.

We also find that existing farm practices influence the adoption of solar irrigation. Respondents who had not implemented the use of fertilisers or pesticides on their farms were more likely prefer the status quo rather than investing into solar irrigation. We could not find that respondent age, gender, other work practices or the number of productive cocoa trees had an influence on preferences for the adoption of solar irrigation. In contrast, Anning et al. (2022) find that off-farm income, gender, and education influence the adoption of various adaptation strategies, indicating adaptation drivers may differ meaningfully from other practices. We find no significant relationship between the number of productive trees and preference for the status quo, unlike Maguire-Rajpaul et al. (2020) who find that cocoa farmers primarily use climate information for shade tree management and that small plot sizes do not incentivise (solar-)irrigation adoption.

Our logistic regression does not indicate multicollinearity amongst independent variables (see Table C.2). This was assessed using the variance inflation factor (VIF), which quantifies how much the variance of a regression coefficient is inflated due to correlation with other predictors. According to James et al. (2021), a VIF value exceeding five is indicative of problematic multicollinearity.

Table C.2
Variance inflation factors (VIF) to assess multicollinearity among independent variables of the logistic regression.

Logistic regression independent variables	VIF
Age in years	1.085
Gender (female)	1.236
Household size in number of people	1.130
Productive cocoa trees (in hundreds)	1.189
Do other work	1.136
Do fertiliser & pesticides	1.128
Stated ignored costs	1.156
Media usage	1.168
Reality	1.284
Predict	1.136
Causes	1.187

Note: n = 578. According to James et al. (2021) a VIF value that exceeds 5 indicates a problematic amount of collinearity.

C.2. Mixed logit with correlated random parameters

In this section, we report the mixed logit model estimated under the relaxed assumption that the parameters are correlated; that the variance-covariance matrix of the parameters is not necessarily diagonal (Mariel and Meyerhoff, 2018). Table C.3 displays the estimated MMNL for each treatment group and Table C.4 shows the detected covariance between random parameters. The parameter estimates are broadly consistent with those obtained from the more restricted model (Table 4).

The MMNL including accounting for correlated parameters has an overall poorer model fit compared to the specification which does not, in terms of AIC and BIC. Loglikelihood ratio tests were not significant for both treatment groups (treatment group one: $\chi 2(6) = 3.9, p = 0.6902$, treatment group two: $\chi 2(10) = 5.14, p = 0.8816$). Consequently, we proceed with the more restricted model in the main text.

Table C.3
Loan costs per month mixed logit models including correlated random parameters.

Attributes	Treatment group one: Rainfall information[a]			Treatment group two: Rainfall and dry day information [a]		
	Mean estimate (rob. s.e.)	St. Dev. estimate (rob s.e.)	Median WTP - GH₵ per month[b] [95% CI]	Mean estimate (rob. s.e.)	St. Dev. estimate (rob s.e.)	Median WTP - GH₵ per month[b] [95% CI]
	-9.487 ***	9.062 ***		-12.270 ***	9.666 ***	
ASC	(2.301)	(1.926)		(3.200)	(2.608)	
	0.033	0.182 *		-0.086	0.160	
Rainfall (in hundreds)	(0.061)	(0.083)		(0.058)	(0.105)	
	0.192	0.478		0.210 *	0.271	7.00
Forecast spread (in hundreds)	(0.109)	(0.247)		(0.097)	(0.152)	[-194.14, 124.30]
				0.059 *	0.086	1.88
Dry days	N/A	N/A	N/A	(0.030)	(0.046)	[-82.75, 132.87]
	3.412 ***	2.533 ***	112.98	3.625 ***	2.392	133.06
Fraction irrigated	(0.361)	(0.367)	[-38.34, 895.63]	(0.305)	(0.381)	[-39.08, 1132.34]
	-3.574 ***	0.582		-3.720 ***	0.784	
Loan cost (log) per month	(0.114)	(0.206)		(0.132)	(0.119)	
Model statistics						
No. individuals	280			298		
No. observations	1680			1788		
AIC	2254.54			2324.88		
BIC	2341.36			2445.64		
Log-likelihood	-1111.27			-1140.44		

[a] Rob. s.e. denote robust standard errors and are calculated using the Delta method due to the correlated random parameters (Mariel et al., 2025; Mariel and Meyerhoff, 2018). Rob. t-ratio and CI refer to t-statistics and 95% confidence intervals, respectively. Model was estimated using 20,000 Sobol draws. Two-sided significance is indicated with asterisks: *** = p<0.001, **= p<0.01, *=p<0.05. Rainfall, forecast spread, irrigated fraction, and loan cost were scaled by 1/100; coefficients are interpreted per 100 units. The loan cost coefficient is log transformed, ln(coefficient) and normally distributed with mean m and variance s, and hence a comparable mean is exp(m + s/2), variance is exp(2m + s) [exp(s) − 1] (Train, 2009). All other coefficients are normally distributed.

[b] WTP is calculated using the Krinsky and Robb, 1990, 1986 method with 10,000 draws

Table C.4
MMNL random parameter covariance.

Covariance matrix x, y	Treatment group one: Rainfall information	Treatment group two: Rainfall and dry day information
	Estimate (Rob. s.e.)	Estimate (Rob. s.e.)
Forecast spread, Rainfall	0.439 (0.272)	0.241 (0.274)
Dry days, Rainfall	N/A	0.071 (0.056)
Dry days, Forecast spread	N/A	0.020 (0.063)
Fraction irrigated, Rainfall	0.459 (0.634)	0.643 (0.747)
Fraction irrigated, Forecast spread	0.846 (0.673)	0.386 (1.362)
Fraction irrigated, Dry days	N/A	2.174 *** (0.428)
Loan cost, Rainfall	0.060 (0.263)	0.706 (0.444)
Loan cost, Forecast spread	0.298 (0.297)	0.309 (0.916)
Loan cost, Dry days	N/A	0.068 (0.330)
Loan cost, Fraction irrigated	0.458 ** (0.150)	0.079 (0.101)

Notes: Corresponding MMNL random parameters are reported in Table C.3. Rob. s.e. denote robust standard errors.

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Appendix D. Additional information on willingness to pay estimates

In this section, we elaborate on the comparison of current costs for solar irrigation in Ghana and our willingness to pay (WTP) estimates from main paper (mixed logit model, MMNL, in Table 4 and latent class multinomial logit model, LC-MNL, in Table 7). For clarity, we include Table D.1 to summarise the WTP values which will be used for the comparison to current costs of solar irrigation.

Table D.1
WTP for a fully irrigated farm, per hectare.

Treatment group	Model	Class	WTP median	WTP confidence interval	
				Lower	Upper
1	LC-MNL	A	11,083	8,966	13,722
1	LC-MNL	B	6,898	3,094	13,793
2	LC-MNL	A	12,342	10,018	15,310
2	LC-MNL	B	N/A	N/A	N/A
1	MMNL	N/A	12,769	7,870	20,447
2	MMNL	N/A	14,493	10,813	19,441

Notes: WTP Estimates are for fraction of farm to be irrigated from main paper Table 4 and Table 7. We have rescaled WTP values to be interpreted as WTP for a fully irrigated farm, per hectare of land. For treatment group two LC-MNL class B the WTP estimates were not significant and have therefore not been included.

The total cost of solar irrigation implementation in Ghana for 2024, as included in our DCE attribute level, was GH₵ 140,000. Recent formal quotations from solar irrigation providers indicated that costs rose in 2025 to approximately GH₵ 195,000, and to GH₵ 250,000 when water storage tanks were included. Based on these updated cost estimates, monthly loan payments for various loan durations were calculated using the following formula:

$$Monthly\ payment = \frac{present\ value * periodic\ interest\ rate}{1 - (1 + periodic\ interest\ rate)^{-total\ number\ of\ interest\ periods}}$$

Where the periodic interest rate is equivalent to annual percentage rate divided by the number of interest periods per year. To ensure comparability with our WTP estimates, the loan calculations applied the same annual interest rate as was used in the DCE design, namely 20% compounded annually. Table D.2 shows the resulting monthly loan costs of a solar irrigation system according to varying loan durations.

Table D.2
Monthly loan costs per loan duration.

Loan duration	Cost estimates for solar irrigation system implementation per hectare		
	2024 cost: GH₵ 140,000	2025 cost excluding water storage tank: GH₵ 195,000	2025 cost including water storage tank: GH₵ 250,000
1	12,969	18,064	23,159
2	7,125	9,925	12,724
3	5,203	7,247	9,291
4	4,260	5,934	7,608
5	3,709	5,166	6,623
6	3,353	4,671	5,988

Note: Monthly loan costs were calculated based on fixed, annually compounded interest rate of 20%.

Using our WTP estimates (Table D.1) and monthly loan costs based on market prices for solar irrigation implementation (Table D.2), we give an indication of the required financial support for farmers such that they could afford solar irrigation adoption. In Fig. D.1, loan durations where market priced loan costs (solid lines) exceed our model estimated WTP estimates (dashed lines) indicate that farmers' WTP would be insufficient to accept a solar irrigation loan, implying a need for subsidies or other financial support to facilitate adoption. In Table D.3 we elaborate on these differences.

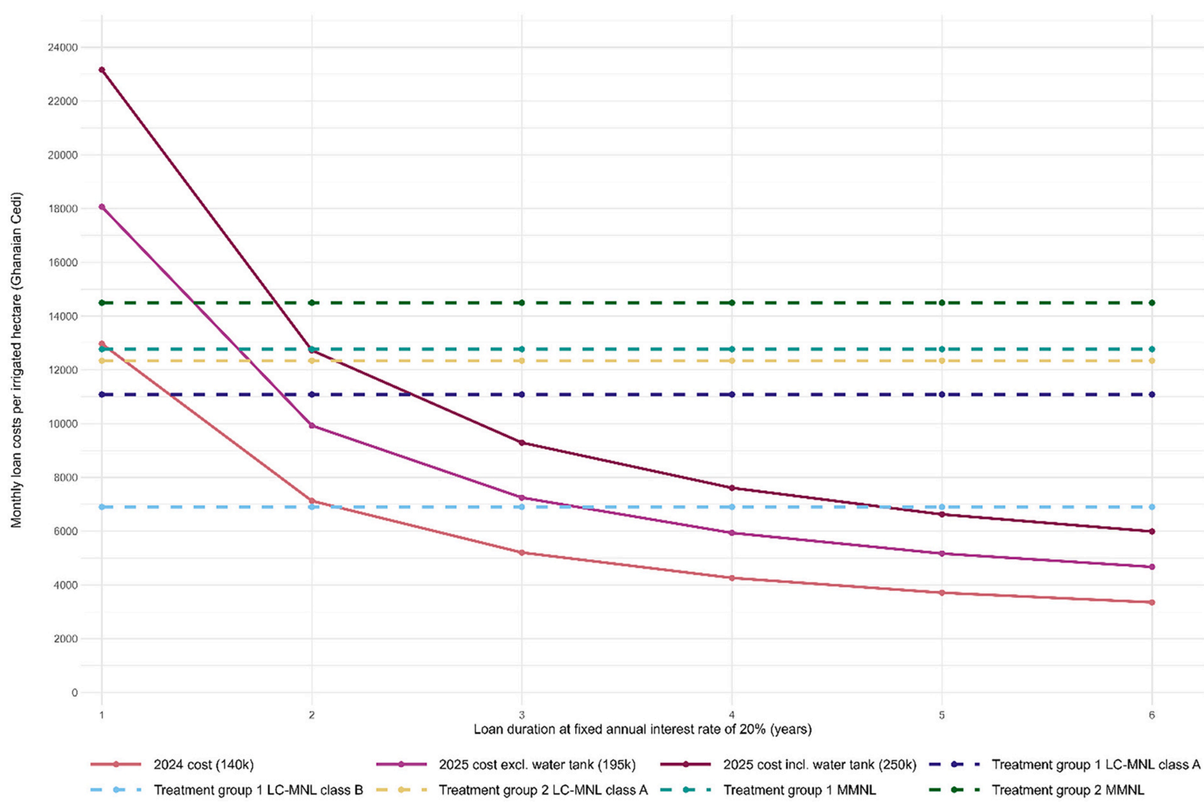

Fig. D.1. Comparison of WTP and market-priced monthly loan costs per irrigated hectare.

Although the magnitude of the required financial support differed across model estimates, a one-year loan for solar irrigation based on 2025 prices was not feasible under any model specifications given our estimated WTP per month per hectare (Table D.3). Using the 2025 cost estimate for solar irrigation implementation, with and without a water storage tank, the one-year loan scenario consistently showed positive values in the corresponding table row, indicating that monthly positive financial assistance or a subsidy that would be required. For example, with monthly payments of GH₵ 18,064 per hectare, respondents in treatment group One LC-MNL Class A were willing to pay only GH₵ 11,083 per month per hectare, resulting in a financing gap of GH₵ 6,891 per month. We see that across all loan amounts, treatment group one LC-MNL Class B are least WTP and hence would require most financial assistance to encourage loan uptake for solar irrigation implementation. In the case of treatment group two LC-MNL Class A, for the loan costs including a water storage tank, a one and two-year loan would require financial assistance, but a three-year loan would not, as the lower monthly per hectare payments (GH₵ 9,291) are below our estimated monthly WTP per hectare of GH₵ 12,342. When we consider the confidence intervals for our WTP estimates, it is no longer clear whether respondents would be willing to accept the loan conditions.

Table D.3
Difference between current market loan costs per month, per hectare and model estimated WTP loan costs per month, per hectare.

Loan duration	2024 loan cost (GH₵ 140k)	Market loan costs - Estimated WTP costs				
		Treatment group 1 LC-MNL class A	Treatment group 1 LC-MNL class B	Treatment group 2 LC- MNL class A	Treatment group 1 MMNL	Treatment group 2 MMNL
1	12,969	1,886	6,071	627	200	-1,524
2	7,125	-3,958	227	-5,217	-5,644	-7,368
3	5,203	-5,880	-1,695	-7,139	-7,566	-9,290
4	4,260	-6,823	-2,638	-8,082	-8,509	-10,233
5	3,709	-7,374	-3,189	-8,633	-9,060	-10,784
6	3,353	-7,730	-3,545	-8,989	-9,416	-11,140
Loan duration	2025 loan cost excluding water storage tank (GH₵ 195k)	Market loan costs - Estimated WTP costs				
		Treatment group 1 LC-MNL class A	Treatment group 1 LC-MNL class B	Treatment group 1 LC- MNL class A	Treatment group 1 MMNL	Treatment group 2 MMNL
1	18,064	6,981	11,166	5,722	5,295	3,571
2	9,925	-1,158	3,027	-2,417	-2,844	-4,568
3	7,247	-3,836	349	-5,095	-5,522	-7,246
4	5,934	-5,149	-964	-6,408	-6,835	-8,559
5	5,166	-5,917	-1,732	-7,176	-7,603	-9,327
6	4,671	-6,412	-2,227	-7,671	-8,098	-9,822
Loan duration	2025 loan cost including water storage tank (GH₵ 250k)	Market loan costs - Estimated WTP costs				
		Treatment group 1 LC-MNL class A	Treatment group 1 LC-MNL class B	Treatment group 2 LC- MNL class A	Treatment group 1 MMNL	Treatment group 2 MMNL
1	23,159	12,076	16,261	10,817	10,390	8,666
2	12,724	1,641	5,826	382	-45	-1,769
3	9,291	-1,792	2,393	-3,051	-3,478	-5,202
4	7,608	-3,475	710	-4,734	-5,161	-6,885
5	6,623	-4,460	-275	-5,719	-6,146	-7,870
6	5,988	-5,095	-910	-6,354	-6,781	-8,505

Note: Green text indicates where loan costs per month per hectare are greater than our estimated farmer WTP for loan costs per month per hectare, indicating insufficient WTP. All values in columns other than loan duration are monthly, per hectare.

Data availability

The data that has been used is confidential.

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