Climate Risk Management 49 (2025) 100720

Contents lists available at ScienceDirect

Climate Risk Management

journal homepage: www.elsevier.com/locate/crm

Farmers' climate change perceptions in central Colombia: A propensity score matching approach using protection motivation theory and psychological distance

Alexander Cano [a,*], Bente Castro-Campos [b,c]

[a] International PhD Program in Agricultural Economics, Bioeconomy and Sustainable Food Systems (IPPAE), Justus Liebig University Giessen, Senckenbergstrasse 3, 35390 Giessen, Germany
[b] Justus Liebig University Giessen, Department of Agricultural Policy and Market Research, Senckenbergstrasse 3, 35390 Giessen, Germany
[c] Center for International Development and Environmental Research (ZEU), Senckenbergstrasse 3, 35390 Giessen, Germany

ARTICLE INFO

Keywords:
Climate change perceptions
Extreme weather events
Droughts
Landslides
Colombia

ABSTRACT

This study investigates how farmers' experiences with extreme weather events, specifically landslides and droughts, shape their perceptions of climate change in central Colombia, and their implications for climate risk management. Using Protection Motivation Theory and psychological distance as frameworks, we surveyed 360 farmers in 2022–2023 to assess their perceptions of climate change severity, vulnerability, and proximity. To control for confounding factors, we employed propensity score matching, comparing farmers in villages affected by landslides and droughts with those in unaffected villages. Our findings reveal that while landslides do not significantly alter farmers' perceptions, droughts heighten awareness of climate change, with statistically significant differences observed in 10 out of 16 perception categories. This suggests that the nature of extreme weather events plays a crucial role in shaping climate change perceptions. Notably, farmers affected by drought perceive climate change as more severe, feel more vulnerable, and report closer psychological distance to its impacts compared to those in landslide-affected areas. These results imply that climate risk management strategies should be tailored to the specific types of extreme weather events affecting a region. Furthermore, by comparing drought and landslide events, this study provides new insight into how different climatic shocks shape farmers' perceptions, contributing to a more nuanced understanding of climate change adaptation. This research highlights how propensity score matching, by better balancing groups and reducing bias from confounding, offers a methodological improvement over conventional approaches in climate perception studies.

1. Introduction

Farmers are particularly vulnerable to the impacts of climate change due to their reliance on weather patterns and natural resources (Miller et al., 2021; Quaye et al., 2018; Skevas et al., 2022). This vulnerability is characterized by an increase in both the frequency and intensity of extreme weather events (Muench et al., 2021). Furthermore, farmers' experiences with these types of events are strongly correlated with their beliefs about climate change (Dai et al., 2015). However, the effects of climate change are not uniform, with

* Corresponding author at: Max-Reger-Strasse 1, 35392 Gießen, Germany.
E-mail addresses: Alexander.Cano@agrar.uni-giessen.de (A. Cano), Bente.Castro-Campos@agrar.uni-giessen.de (B. Castro-Campos).

https://doi.org/10.1016/j.crm.2025.100720
Received 13 December 2024; Received in revised form 19 May 2025; Accepted 11 June 2025
Available online 12 June 2025
2212-0963/

variations observed even within the same geographic region (Epanchin-Niell et al., 2017; Gupta et al., 2020).

Climate change is often perceived as an abstract, distant, and gradual phenomenon, making it less likely to elicit immediate concern or prompt action (Ricart et al., 2023). In contrast, extreme weather events provide tangible evidence of climate change's impacts (Bergquist et al., 2019). These firsthand experiences can significantly shape farmers' beliefs. It has been found that farmers in regions where different extreme weather events have occurred tend to have a stronger belief in climate change (Borick & Rabe, 2017; Dai et al., 2015). Moreover, farmers' perceptions of threats strongly influence their adaptive behaviors (Mosavian et al., 2023), making it essential to understand how different environments affect climate change perceptions.

The connection between personal experience and perception is pivotal in addressing the impacts of climate change, particularly in agricultural contexts. This underscores the need for strategies that bring climate change closer and more tangible to farmers (Yazdanpanah et al., 2023). As climate change continues to accelerate, it is essential to conduct spatial assessments of its impacts to facilitate better-informed decision-making that can preemptively mitigate its damages (Venkatappa et al., 2021). Understanding farmers' perceptions of climate change and extreme weather events is crucial for designing effective climate change measures (Fahad et al., 2020).

The central region of Colombia, located between the central and western Andean mountain ranges, serves as an ideal setting to examine the intersection of climate change impacts and agricultural practices. This region is particularly susceptible to extreme weather events, such as landslides and droughts, due to its diverse topography and resulting climatic variations, which pose significant challenges for agricultural activities. Rainfall is the main trigger for landslides in the area, accounting for 87 % of such events and being one of the main causes of socio-economic losses (Aristizábal & Sánchez, 2020; Garcia-Delgado et al., 2022). On the other hand, droughts, characterized by prolonged periods of low precipitation, exacerbate agricultural vulnerability by leading to crop failure and diminished water resources (Freire-González et al., 2017).

We use Protection Motivation Theory (PMT) and the concept of psychological distance as theoretical frameworks, given their significance in the climate adaptation literature (Cano & Castro Campos, 2024). PMT suggests that individuals' responses to threats are shaped by their perceptions of severity, vulnerability, and efficacy (Rogers, 1983). Additionally, the concept of psychological distance refers to how far away a threat feels across temporal, spatial, social, and hypothetical dimensions (Liberman et al., 2007). These theoretical constructs allow us to examine how farmers perceive and respond to climate-related risks based on both internal (perceptions) and external (observed weather shocks) factors. While previous studies have examined farmers' perceptions using these theories, they typically focus on a single type of event (see Bergquist et al., 2019; Li et al., 2023; Rodríguez-Cruz & Niles, 2021), few studies have directly compared the influence of distinct types of extreme weather events on perceptional outcomes through a quasi-experimental approach.

To address this gap, we employ Propensity Score Matching (PSM) to reduce selection bias and create comparable groups of farmers exposed to different climate shocks. This methodological choice strengthens the causal interpretation of the results, which is often limited in perception studies due to confounding factors (Austin, 2011a; Caliendo & Kopeinig, 2008; Stuart, 2010). By combining these theoretical constructs with a quasi-experimental design, this study offers new evidence on how specific weather experiences –landslides and droughts- shape farmers' perceptions of climate change severity, vulnerability, and distance.

The study makes three key contributions. First, it enhances our understanding of how different types of extreme weather experiences influence climate change perceptions across psychological constructs. Second, it applies a matching methodology rarely used in this context, improving the internal validity of results. Third, it provides empirical evidence from a climate-vulnerable region in the so-called Global South, which remains underrepresented in the behavioral adaptation literature (Cano & Castro Campos, 2024).

This study has two main objectives: (1) to examine differences in climate change perceptions between farmers in villages affected by extreme weather events (landslides and droughts) and those in unaffected villages, and (2) to compare climate change perceptions between farmers in landslide-affected villages and those in drought-affected villages. To achieve these objectives, PSM is used to control for confounding variables and isolate the effect of extreme weather events.

This article is structured as follows. Section 2 provides the theoretical background of the PMT and psychological distance used in this research. In section 3, we detail the methods, variables, and propensity score matches employed. Section 4 presents the results, followed by the discussion in section 5. We draw conclusions in section 6.

2. Theoretical background

Previous research in Colombia has examined how different populations perceive climate change and respond to its effects. These studies highlight the importance of contextual factors, including geography, livelihoods, and access to information, in shaping local interpretations of climate-related risks. For example, in Bogotá, Pardo Martínez et al. (2018) found widespread public awareness of climate change, with droughts and floods identified as major threats to health, water access, and food security. Similarly, Rodríguez Pacheco et al. (2022) analyzed perceptions among university students in the Caribbean region and found that, while students generally understood the causes and global implications of climate change, many struggled to relate these processes to their local realities.

In rural areas, climate change perceptions are often shaped by their context. Botero et al. (2021), for example, used latent class analysis to identify heterogeneous perception profiles among bean farmers in Santander. They found that farmers located at lower altitudes and farther from urban centers expressed greater concern about the future economic consequences of climate change and were more likely to seek out climate information, suggesting higher receptivity to adaptive measures such as drought-resistant seeds. In Manizales, Barrucand et al. (2017) studied coffee growers and observed that although many had limited prior knowledge of climate change, they had experienced noticeable changes in rainfall and temperature patterns and were adapting using a combination of traditional knowledge, such as placing rocks to slow the flow of running water and reduce soil erosion, and institutional support, including agricultural extension services provided by government agencies and coffee grower associations.

In the Sierra Nevada del Cocuy-Güicán, Alcántara Rodríguez et al. (2018) reported that farmers were concerned about the degradation of páramo vegetation and attributed environmental threats to both climate variability and unsustainable land use practices. Meanwhile, in rural Eastern Andes communities, Murtinho et al. (2013) found that Water User Associations primarily attributed water scarcity to deforestation rather than climate change. Notably, this perception diverged from meteorological data, highlighting how subjective interpretations of environmental change may differ from technical diagnoses.

Taken together, these studies illustrate the diversity of climate change perceptions across both urban and rural Colombia. However, few have systematically applied theoretical frameworks to explain how these perceptions emerge from individuals' lived experiences. Our study directly addresses this gap by integrating Protection Motivation Theory and psychological distance to analyze how farmers' exposure to droughts and landslides shapes their climate change perceptions. By combining these complementary theoretical frameworks, our approach advances a more robust and theoretically grounded understanding of the psychological processes driving climate perception in rural contexts.

2.1. Protection motivation theory (PMT)

This theory, originally proposed by Rogers (1975), suggests that individuals' attitudes change when they face fear-inducing events. Fear appeals have three main components: (1) the magnitude or severity of an event; (2) the likelihood of this event occurring; and (3) the effectiveness of the protective response to this event. Information about these components serves as a stimulus, prompting cognitive processes that motivate individuals to take action to avoid the threat. Essentially, fear appeals communicate the negative consequences of not following the recommended actions, encouraging individuals to adopt behaviors that mitigate the perceived danger.

The theory was updated by Rogers (1983), including different sources of information that can initiate the cognitive processes. These sources are either environmental or intrapersonal. In environmental sources, learning is observational, which implies that individuals observe their surroundings and what happens to others; it also includes verbal persuasion from other people. Intrapersonal sources consist of personal variables or past experiences with similar events that pose a comparable threat. Regardless of the information source, two key appraisal processes are initiated: threat appraisal and coping appraisal. The threat appraisal involves evaluating the severity of the threat and one's vulnerability to it. The coping appraisal assesses the ability to manage and avoid the threat, including the belief in the effectiveness of the recommended response and the associated costs. Additionally, self-efficacy, or the belief in one's capacity to successfully adopt the protective measure, was incorporated into the theory by Maddux and Rogers (1983).

According to PMT, an individual's protective motivation is determined by the combined effects of their threat and coping appraisal processes. Protective motivation, as measured through behavioral intention, is assumed to be a positive linear function of four key factors: (1) the severity of the threat, (2) personal vulnerability to the threat, (3) the ability to perform the coping response, and (4) the effectiveness of the coping response in avoiding the threat (Rogers, 1983). This linear function is a major assumption of the theory. Furthermore, an additive model applies within each appraisal process (threat appraisal and coping appraisal). However, when combining the two processes, second-order interaction effects occur. This means that the elements of one appraisal can influence how the components of the other appraisal affect motivation.

This theory has been widely used to explain climate change adaptation behaviors, particularly in agricultural settings, revealing that constructs such as perceived severity and perceived vulnerability are positively associated with farmers' intentions to adopt protective measures. For instance, empirical evidence shows that exposure to drought conditions increases both risk perception and behavioral intentions (Gebrehiwot & van der Veen, 2021), while perceptions of risk and adaptation efficacy jointly shape intentions to adopt technologies (Dang et al., 2014). Other studies highlight that the way farmers receive and process risk information, such as drought communications, can strengthen adaptation appraisal more than risk appraisal itself (Sutcliffe et al., 2024), and that socio-cognitive factors also influence adaptation intentions (Rodríguez-Barillas et al., 2024). Our study builds on this literature by operationalizing key PMT constructs in a context where different climate shocks—specifically droughts and landslides—are analyzed separately. This approach allows for a more nuanced understanding of how severity and vulnerability appraisals are shaped by the specific nature of each threat.

2.2. Psychological distance

Liberman and Trope (2014, p. 365) define psychological distance as "the extent of divergence from direct experience of me, here and now along the dimensions of time, space, social perspective, or hypotheticality". According to them, individuals use mental representations of different events or situations. These representations are categorized into high-level construals, which are abstract and focus on the most important, general aspects of an event, and low-level construals, which are concrete and focus on specific details (Liberman & Trope, 1998). Additionally, Trope and Liberman (2003) propose that temporal distance (how close or far in the future individuals see the event) changes how individuals mentally represent these events. The greater the temporal distance, the more likely to be represented in high-level construals rather than low-level construals.

Besides the temporal distance, other types of distances affect how individuals interpret an event based on their perceived divergence from it (Bar-Anan et al., 2006). For example, the closer the spatial proximity (spatial distance) of an event, the more specific and concrete the mental representation of the event (Trope et al., 2007). Social distance refers to the perceived similarity between individuals; the more similar people feel to others, the less socially distant they feel, leading to a more specific and concrete interpretation (Liberman et al., 2007). Finally, hypothetical distance pertains to the likelihood of an event occurring. Improbable or hypothetical events are perceived more abstractly, whereas certain events are viewed more concretely (Bar-Anan et al., 2006). Individuals anchor their interpretations in their actual experiences and then extend to more abstract, hypothetical scenarios.

In the context of extreme weather events, these psychological distances play a significant role in shaping how farmers perceive and respond to climate change (Azadi et al., 2019). Farmers who have directly experienced events like droughts or landslides tend to view climate change more concretely and immediately. Their interpretation is shaped by a close, immediate perspective due to the spatial and temporal distance of these events. This proximity may lead to heightened awareness and concern, influencing their decision-making and adaptive behaviors (Liberman et al., 2007). On the other hand, farmers who have not personally experienced such events may see climate change as a distant, abstract concept, focusing on big-picture ideas rather than specific, immediate details. This psychological distance can result in less urgency in their responses to climate-related risks, affecting their engagement in mitigation or adaptation strategies. Understanding these dynamics is essential for designing effective interventions that consider farmers' differing perceptions and psychological distances, both of which shape the collective reality within affected communities.

This study contributes to the literature by applying the concept of psychological distance in a rural setting highly exposed to climate variability. While prior research has explored the role of psychological distance in shaping climate change perceptions, much of it has focused on broader national samples or urban populations. Some studies have shown that reduced psychological distance increases the perceived relevance of climate threats and can trigger stronger emotional responses, while greater distance tends to elicit weaker engagement (Chu & Yang, 2019). Others suggest that exposure to locally relevant stimuli can reduce perceived socio-spatial distance and enhance personal relevance, particularly among individuals already concerned about climate change (Halperin & Walton, 2018). Additionally, while reducing distance can enhance personal engagement, the effectiveness of such strategies may vary depending on individuals' prior beliefs or global identity salience (Loy & Spence, 2020). Most existing studies address general perceptions of climate change without explicitly comparing how different types of extreme weather experiences, such as droughts and landslides, affect psychological distance across multiple dimensions (Keller et al., 2022). By examining farmers' perceptions in communities affected by different climate shocks, our study offers new insights into how spatial, temporal, social, and hypothetical dimensions of psychological distance may shift depending on the nature of the environmental threat. This focus enhances the understanding of how specific experiences shape mental representations of climate change, which is critical for designing context-sensitive adaptation strategies.

3. Methods

3.1. Average treatment effect on the treated

We consider farmers living in villages where different extreme weather events (landslides and droughts) have been experienced. Our objective is to measure how residing in these places affects their perceptions of climate change. To measure this effect, we define treatment $T_i = 1$ if farmer i receives the treatment and zero otherwise, and $Y_i(T_i)$ corresponds to their outcomes under each treatment condition for each farmer. The effect that the treatment has on a given farmer can be written as

$$\tau_i = Y_i(1) - Y_i(0) \tag{1}$$

Since causal effects are estimated based on the response after receiving a treatment, it is not possible to observe the response of the same farmer would have had if they had not received the treatment, creating a lack of a counterfactual. As a result, estimating causality is a missing data problem (Rosenbaum & Rubin, 1983). Due to the absence of a counterfactual for each farmer, the treatment effect cannot be estimated at the individual level (τ_i), and is often estimated as the average effect across a group or population (Caliendo & Kopeinig, 2008). One way to assess this is by calculating the difference in the expected values of outcomes between those who received the treatment and those who did not. This is known as the Average Treatment Effect (ATE).

$$\tau_{ATE} = E(\tau) = E[Y(1) - Y(0)] \tag{2}$$

The ATE estimates the average effect across the entire sample, regardless of whether individuals receive the treatment. However, since our focus is understanding specifically how extreme weather events have affected the climate change perceptions of the farmers who have directly experienced them, we estimate the Average Treatment Effect on the Treated (ATET), which specifically examines the subset of the population that received the treatment—in this case, those farmers residing in a village where landslides or droughts have occurred.

$$\tau_{ATET} = E[\tau|D = 1] = E[Y(1)|D = 1] - E[Y(0)|D = 1] \tag{3}$$

The expected value of the ATET is the difference between expected outcome values with and without treatment for those who received the treatment. By focusing specifically on individuals who received the treatment, this parameter reveals the direct impact on the outcome variable (Caliendo & Kopeinig, 2008; Heckman et al., 1999).

3.2. Propensity score matching (PSM)

To estimate the ATET we employ PSM, as it allows us to make inferences about treatment effects using observational data. The first step is to calculate the propensity score (PS), which is the probability of a farmer living in a village affected by extreme weather events. The PS is calculated as a probit model of a set of observable covariates that can influence both exposures to the treatment and their perceptions of climate change. In our study, we have two mutually exclusive treatments due to the characteristics of our sample, as detailed in section 3.4. For this reason, we estimate two different PSs for each event. The first is that farmers live in a village where three or more landslides have occurred (Equation (4). The second is that farmers live in villages where two or more droughts have occurred (Equation (5).

$$p(X_i) = Pr(L_i = 1|X_i) \tag{4}$$

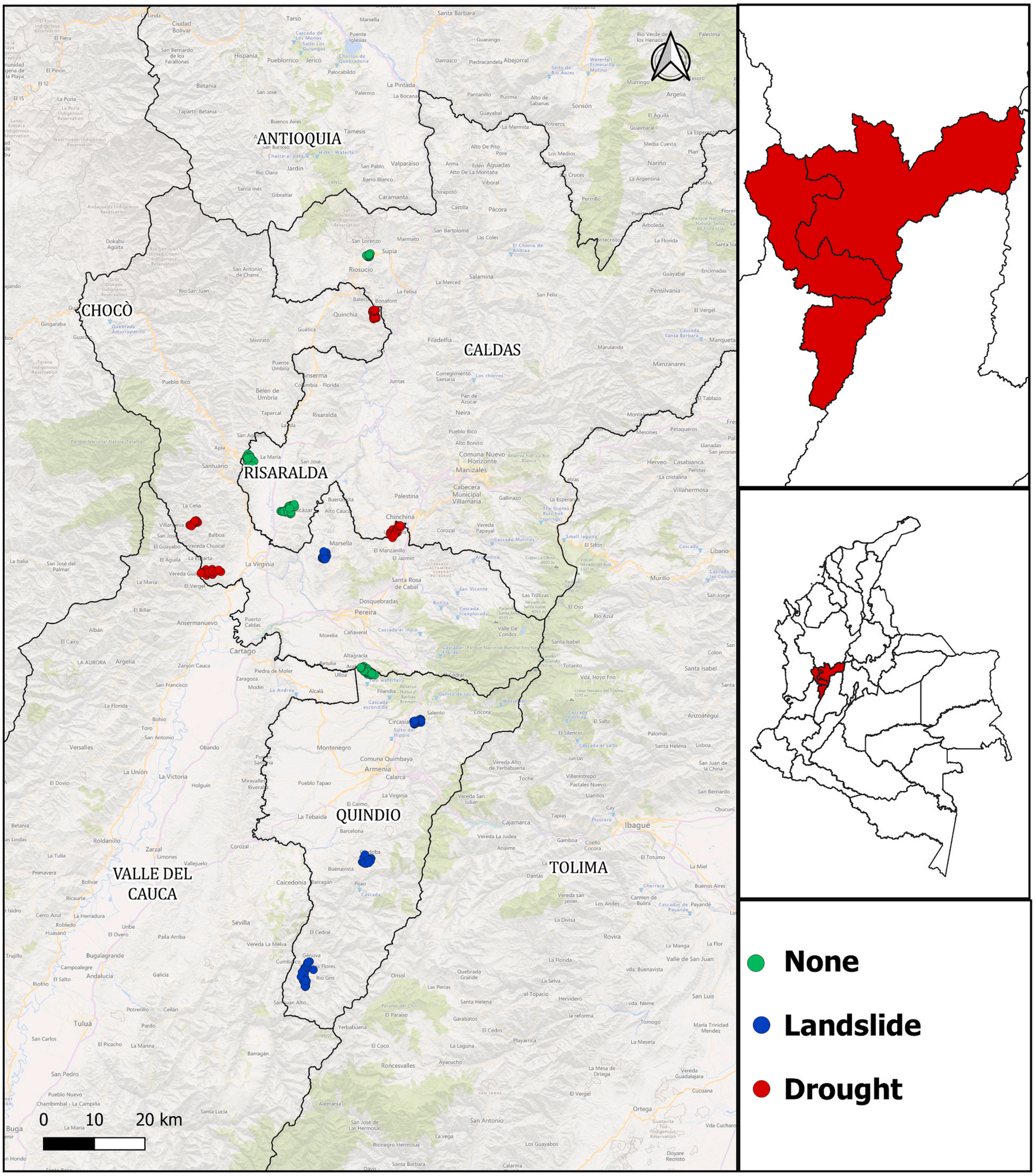

Fig. 1. Research Locations in Central Colombia. .
Source: Authors based on fieldwork conducted by Cano from Nov 2022 to Feb 2023.

$$p(X_i) = Pr(D_i = 1|X_i) \tag{5}$$

Where L_i represents whether the farmer lives in a village where landslides have occurred and D_i if they reside in a village where droughts have happened. X_i are the observable characteristics of the farmers, which include demographic variables (such as age, gender, education level, and income), farm characteristics (size and number of workers), and the natural resource endowment on their farm (e.g., having a water source on the farm or access to a water source, and having forest or part of a forest on their land).

Once the PS is estimated, matching is performed. This process consists of matching farmers who have been exposed to extreme weather events with those who have not, based on the similarity of their observable characteristics. Since we have not considered villages where both extreme events have occurred, farmers who live in villages affected by landslides have not been affected by drought, so they are used as a control group for those who have experienced drought, and vice versa. The goal of matching is to create a control group comparable to the treated group, thus minimizing bias in the estimation of causal effects (Cameron & Trivedi, 2005). By matching individuals with similar PS, the distribution of covariates between the groups is balanced (Caliendo & Kopeinig, 2008), which facilitates a more accurate comparison of the impact of the treatment, i.e., living in a landslide or drought-affected village, on perceptions of climate change.

We employed two matching techniques to ensure robust comparisons. The first is nearest-neighbor matching, where each farmer who has experienced an extreme weather event is matched with the closest untreated farmer in terms of their PS. This approach helps ensure that the pairs are as comparable as possible. The second technique is caliper matching. This method introduces an additional constraint by allowing matches only if the difference between the PS of the matched pairs falls within a predefined range, known as the caliper, minimizing the risk of mismatching by excluding pairs with overly disparate PS (Caliendo & Kopeinig, 2008). Following the usual procedure of estimating the caliper as 0.2 times the standard deviation of the PS (Austin, 2011b; Garrido et al., 2014; Harder et al., 2010), we set the caliper at 0.010 for the landslides group and 0.020 for the droughts given their different standard deviations.

3.3. Hypotheses

Based on this matching process, we aim to test the following hypotheses as explained in sections 3.1. and 3.2., respectively:

H1: There is no significant difference in climate change perceptions (perceived severity, perceived vulnerability, psychological distance) between farmers residing in villages that have experienced extreme weather events and those in villages that have not.

H2: There is no significant difference in climate change perceptions between farmers residing in villages affected by landslides and those affected by droughts.

Estimating these hypotheses can reveal whether direct experience with extreme weather events, such as droughts or landslides, influences farmers' perceptions of climate change severity, vulnerability, and psychological distance. It can also show if the type of extreme event (landslide vs. drought) leads to different perceptions, potentially guiding more targeted communication and intervention strategies.

3.4. Data

All villages in the region where extreme weather events were reported between 2005 and 2021 were identified using public data from Colombia's *Unidad Nacional para la Gestión del Riesgo de Desastres* (UNGRD). Some villages experienced up to six landslides and others up to three droughts. To ensure that only locations with significant and recurrent exposure to climatic shocks were included, thus increasing the likelihood of perceptual differences, we combined proximity to events (Funderburg et al., 2010) with an additional criterion based on event frequency (Pinto et al., 2014). Specifically, we applied a minimum threshold of three landslides and two droughts. This criterion balances empirical and practical considerations: villages with fewer events were considered less likely to show measurable differences in climate risk perceptions, while setting a higher threshold would have drastically reduced the eligible sample. Based on this criterion, four villages with landslide experience, four with drought experience, and four where neither of these events had occurred were randomly selected (Fig. 1). To confirm the classification and coordinate fieldwork, we contacted the municipal agricultural secretariat to verify event exposure and obtain contact information for local leaders. The leaders then confirmed the presence or absence of events, helped schedule the visits, and informed the community about our study.

This design constitutes a quasi-experimental design approach, where farmers are not randomly assigned to treatment or control conditions, but where PSM is later applied to statistically adjust for pre-treatment differences and strengthen causal inference (Dehejia & Wahba, 2002; Estifanos et al., 2020; Goldfarb et al., 2022; Rosenbaum & Rubin, 1983). To preserve internal validity, we excluded villages affected by both types of events to avoid confounding effects and to create three mutually exclusive comparison groups: (1) 120 farmers living in villages where landslides have been experienced, (2) 120 farmers living in villages where droughts have occurred, and (3) 120 farmers living in villages where none of these events have happened. Because the two treatment categories are mutually exclusive, farmers exposed to one type of shock also serve as potential controls for the other. For example, when analyzing the effect of drought exposure, the control group includes both farmers from unaffected villages and those from landslide-affected villages, totaling 240 individuals. The same logic applies when evaluating the effect of landslide exposure. This design maximizes the comparability between treatment and control groups while maintaining internal validity in estimating perceived impacts.

A random sampling approach was used to choose 30 farmers from each of the selected villages, and between 2022 and 2023, a total of 360 farmers were visited and surveyed. This sampling strategy resulted in 120 farmers in each treated group and 240 in the control group for each treatment, achieving a 1:2 ratio that is well-suited for PSM (Kolar & Steiner, 2021; Pirracchio et al., 2012). To further assess the adequacy of the sample size, we conducted a power analysis assuming a moderate effect size of 0.4 standard deviations, a standard deviation of 1, and a significance level of 0.05. The estimated power for detecting group differences is 0.946, which exceeds the conventional 0.8 threshold, indicating that the sample provides sufficient statistical power to detect meaningful effects with 95 % confidence. The decision to survey 30 farmers per village was also based on logistical considerations in rural areas, such as the limited number of active farms per village, and the need to ensure feasibility and balance across comparison groups.

The survey[1] included information on the farmers' perceptions of climate change, incorporating their assessments of the severity, their sense of vulnerability, and their psychological distance. Additionally, it collected socio-demographic data and details about their farm operations. The design of the perceived severity and vulnerability indicators was based on methodological approaches developed by Delfiyan et al. (2021) and Pakmehr et al. (2020). Table 1 provides variable definitions and descriptive statistics. Perceived severity was assessed through three categories: (1) the impact on their farms, (2) the village's natural resources, and (3) other farmers in the village. Each of these was evaluated using a 5-point Likert scale, where 1 = not at all serious and 5 = very serious. Perceived vulnerability was evaluated by asking farmers how frequently they worry weekly about climate change, its impacts, and the effects on their farm operations. Each item was rated on a 5-point Likert scale, where 1 = very little and 5 = a lot.

To assess the psychological distance of climate change, we followed the frameworks proposed by Peng et al. (2022) and Rodríguez-Cruz and Niles (2021), evaluating four dimensions: spatial, temporal, social, and hypothetical. Each was measured using a 5-point Likert scale where farmers indicated their level of agreement with each statement (1 = completely disagree, 5 = completely agree) to capture their perceived distance from climate change. Each dimension was measured with two items that asked respondents whether they view the effects of climate change as near (low psychological distance) or far (high psychological distance). Before full implementation, the survey instrument was pre-tested with 15 farmers from a non-sampled village to assess clarity and contextual relevance. Feedback from the pilot informed minor adjustments in language and ordering of questions. All enumerators had prior experience conducting surveys in rural settings, which facilitated communication and trust with respondents. Nevertheless, they received two days of training specifically focused on the survey protocol, theoretical constructs, and ethical procedures. Surveys were conducted face-to-face, and data entry included double-checking procedures to minimize human error. The internal consistency of the Likert-based indices was tested using Cronbach's alpha. The alpha for the perceived severity variables was 0.815, for the perceived vulnerability was 0.882, and for the psychological distance was 0.843. These values support the reliability of the variables representing each perception type.

The overall sample shows a mean perception of 3.998 (SD 1.241) for how serious the consequences of climate change are for their farm operations. Similarly, for the perceived severity of the impact on the village's natural resources, the mean is 3.768 (SD 1.418); and for the impacts on other farmers, the mean is 4.026 (SD 1.236). When it comes to perceived vulnerability, the mean perception of weekly concern about climate change is 4.046 (SD 1.307). The average perception of concern about the impacts of climate change is 4.085 (SD 1.341). Finally, when it comes to concerns about the negative effects of climate change on agricultural activities, the mean is 3.998 (SD 1.397).

Regarding the psychological distance, the belief that climate change is affecting their village (Spatial 1) has a mean of 4.072 (SD 1.393). In contrast, the perception that climate change affects other villages but not their own (Spatial 2) has a mean of 1.672 (SD 1.293). For the temporal distance, the mean perception that the effects of climate change will occur in the future but are not happening now (Temporal 1) is 1.650 (SD 1.266). Conversely, the belief that the effects of climate change are happening now (Temporal 2) has a mean of 4.354 (SD 1.246). Within the social distance, the belief that climate change is going to affect farmers like them (Social 1) has a mean of 4.619 (SD 0.898). On the other hand, the belief that climate change will affect other farmers but not themselves (Social 2) shows a mean of 1.301 (SD 0.862). For the hypothetical distance, the mean value for the uncertainty about whether climate change is really happening (Hypothetical 1) is 1.662 (SD 1.239). The belief that climate change is already affecting them (Hypothetical 2) has a mean of 4.291 (SD 1.299). The perception that landslides are a consequence of climate change (Hypothetical 3) has a mean of 4.563 (SD 0.972), while the belief that droughts are a consequence of climate change (Hypothetical 4) has a mean of 4.379 (SD 1.193).

The variables used for the PS include several demographic and farm-related factors. On average, the majority of participants (64.2 %) are under 60 years old (SD 0.480) and nearly half of them (48.3 %) were female (SD 0.500). Single farmers accounted for 19.2 % of the sample (SD 0.394). In terms of education, 38.9 % of the sample had attained an elementary education (SD 0.488) and 65.6 % reported earnings below the national monthly wage (SD 0.476). The average number of workers (including family members) per farm is 2.939 (SD 3.352) and 73.30 % of farms are smaller than 5 ha (SD 0.468). Regarding their natural resources endowment, two-thirds (66.1 %) of farmers reported having a natural spring or access to a river, creek, or stream on their farms (SD 0.474). Lastly, 65.6 % of farmers reported that their farms include a forest or bamboo forest, either in whole or in part (SD 0.476).

4. Results

4.1. Balance and test of the PSM

Fig. 2 shows the distribution of PS between the treated and untreated (control) groups for the PS balance analysis of the group of farmers residing in villages where landslides have occurred. Likewise, Fig. 3 shows the distribution, but for the group of farmers living in villages where drought has been experienced. It can be observed that the PS for landslides ranges between approximately 0.1 and 0.5, while that for droughts is between 0.1 and 0.8. The green bars show the distribution of individuals who received the treatment, i.

[1] The survey used in this research is available upon request.

Table 1
Description and Summary Statistics of Variables.

Variables	Description	Pooled		No Event		Landslide		Drought	
		mean	sd	mean	sd	mean	sd	mean	sd
Treatments									
Landslide	1 if the farm is located in a village with 3 or more landslides since 2005; otherwise 0	0.333	0.472						
Drought	1 if the farm is located in a village with 2 or more droughts since 2005; otherwise 0	0.333	0.472						
Perceived Severity	*How negative the consequences of climate change are (1 is "not at all serious" and 5 is "very serious"):*								
Farm	Your farm's agricultural operations	3.998	1.241	3.894	1.312	4.046	1.136	4.054	1.273
Natural Resources	The natural resources of the village	3.768	1.418	3.850	1.359	3.554	1.445	3.900	1.436
Farmers	Other farmers in the village	4.026	1.236	4.067	1.202	3.817	1.230	4.196	1.256
Perceived Vulnerability	*How much do these concern you on a weekly basis (1 is "very little" and 5 is "a lot"):*								
Climate Change	Thinking about climate change	4.046	1.307	3.860	1.386	3.983	1.372	4.296	1.118
Impacts of Climate Change	Being affected by the negative effects of climate change	4.085	1.341	3.925	1.452	3.992	1.405	4.338	1.114
Operation of the Farm	Negative effects on their agricultural activities	3.998	1.397	3.944	1.445	3.888	1.450	4.162	1.285
Psychological Distance	*How much do you agree with the following statements (1 is "completely disagree" and 5 is "completely agree")*								
Spatial 1	Climate change is affecting this village	4.072	1.393	3.948	1.449	4.263	1.228	4.005	1.481
Temporal 2	The effects of climate change are happening right now	4.354	1.246	4.204	1.356	4.412	1.200	4.446	1.172
Social 1	Climate change is going to affect farmers like me	4.619	0.898	4.542	1.042	4.632	0.816	4.683	0.820
Hypothetical 2	Climate change is already affecting me	4.291	1.299	4.096	1.403	4.386	1.209	4.392	1.266
Hypothetical 3	Landslides are a consequence of climate change	4.563	0.972	4.475	1.079	4.633	0.857	4.579	0.968
Hypothetical 4	Droughts are a consequence of climate change	4.379	1.193	4.283	1.270	4.215	1.343	4.638	0.882
Spatial 2	Climate change is affecting other villages, but NOT this village	1.672	1.293	1.742	1.262	1.533	1.161	1.742	1.441
Temporal 1	The effects of climate change are going to happen in the future, but they are NOT happening right now	1.650	1.266	1.796	1.360	1.692	1.289	1.462	1.125
Social 2	Climate change is going to affect other farmers but NOT me	1.301	0.862	1.396	0.881	1.300	0.863	1.208	0.839
Hypothetical 1	I am not sure that climate change is really happening	1.662	1.239	1.608	1.192	1.878	1.386	1.500	1.100
PS Control Variables									
Less than 60 years	1 if the farmer is less than 60 years old; 0 otherwise	0.642	0.480	0.633	0.484	0.633	0.484	0.658	0.476
Female	1 if the farmer identifies herself as a female; 0 otherwise	0.483	0.500	0.508	0.502	0.492	0.502	0.450	0.500
Marital status	1 if the farmer is single; 0 otherwise	0.192	0.394	0.183	0.389	0.200	0.402	0.192	0.395
Education	1 if the maximum level of education attained is elementary education; 0 otherwise	0.389	0.488	0.425	0.496	0.383	0.488	0.358	0.482
Income	1 if their income is less than one national monthly wage; 0 otherwise	0.656	0.476	0.550	0.500	0.692	0.464	0.725	0.448
Workers	Number of workers	2.939	3.352	2.850	3.436	2.767	2.053	3.200	4.216
Farm Size	1 if the size of the farm is less than 5 ha; 0 otherwise	0.733	0.443	0.767	0.425	0.708	0.456	0.725	0.448
Water	1 if the farm has a natural spring or access to a river, creek, stream, etc.; 0 otherwise	0.661	0.474	0.583	0.495	0.708	0.456	0.692	0.464
Forest	1 if the farm has a forest or a bamboo forest, or part of it; 0 otherwise	0.656	0.476	0.733	0.444	0.658	0.476	0.575	0.496
Observations		360		120		120		120	

Source: Authors.

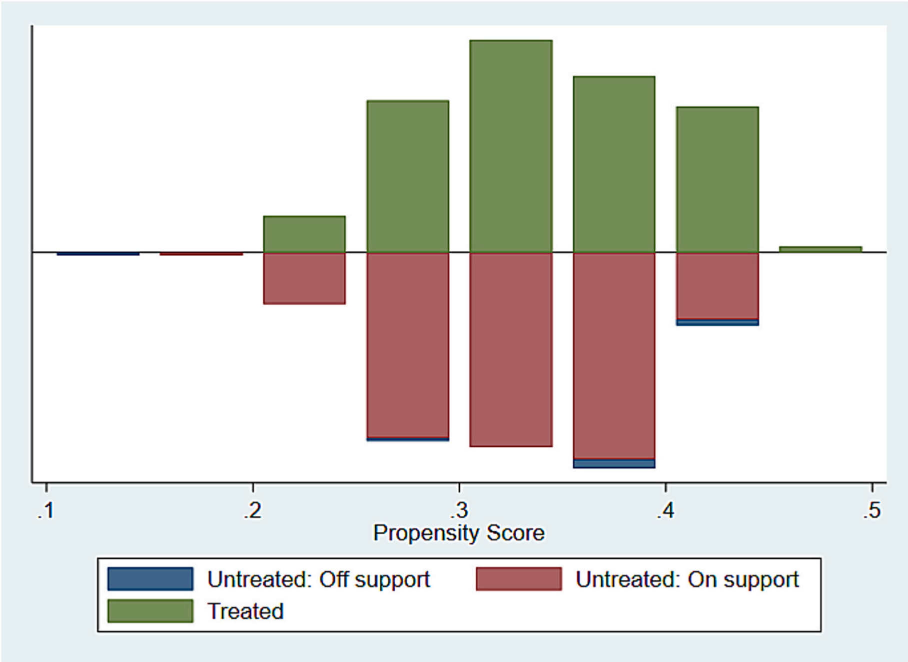

Fig. 2. Propensity Score Balance – Landslides. .
Source: Authors

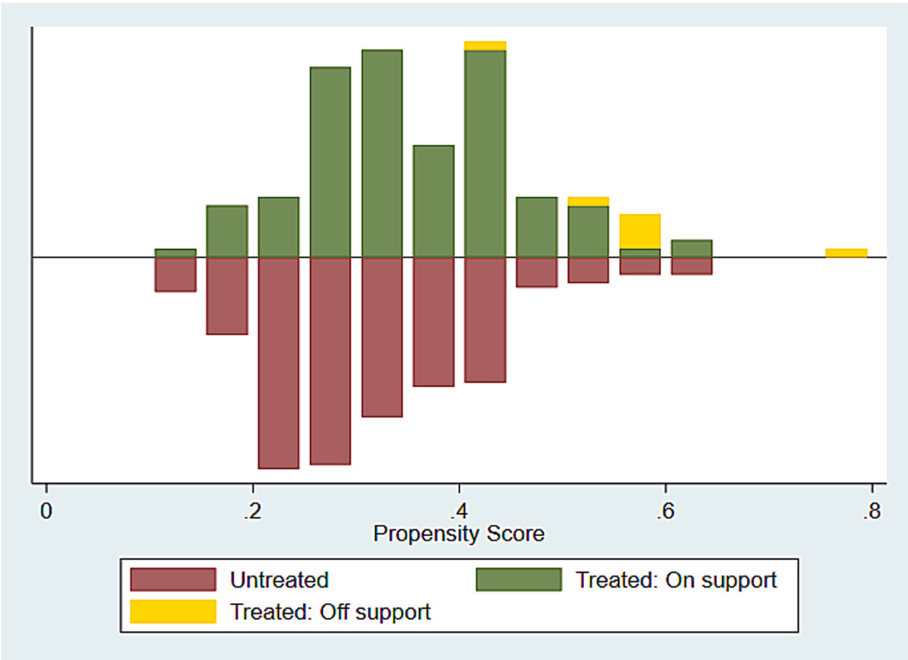

Fig. 3. Propensity Score Balance – Droughts. .
Source: Authors

e., those living in areas affected by landslides or drought. The height of each green bar indicates the number of treated individuals with a given PS range. On the other hand, the red bars represent the distribution of untreated individuals (those not living in landslide- or drought-affected areas) that are within the common support range with treated individuals. These are the control units that have PS comparable to those of the treated, thus allowing for valid matching.

In Fig. 2 the blue bars show the distribution of untreated farmers who are outside the range of common support. Likewise, in Fig. 3, the yellow bars show the distribution of treated farmers who are outside of this range. These farmers have such different PS that they have no comparable counterparts, so it is not considered appropriate to match them. Therefore, they are "out of support" and are not included in the matching analysis. The figures show that in both cases, the presence of red and green bars of similar size within the common support suggests an acceptable balance between the covariates of the matched groups.

Table 2 presents the results of a covariate balance analysis before and after applying PSM for the landslide group and Table 3 for the drought group. This analysis aims to determine if the characteristics (covariates) of farmers living in areas affected by landslides are similar to those of farmers in unaffected areas. We compare these characteristics before matching (unmatched, 'U') and after matching (matched, 'M') to check for balance between the two groups. The bias for all variables is reduced to below 10 %, which aligns with recommended standards for achieving sufficient balance between groups (Austin, 2009). Additionally, most covariates show a significant reduction in bias (%reduct |bias|), indicating better balance. Before matching (unmatched), the "Income" variable showed a bias of 11.5 % in Table 2 **and 22.3** % in Table 3. Bias here means the initial difference in "Income" between the treated group (those in landslide-affected areas) and the control group (those in unaffected areas). After matching, the bias for "Income" reduced to −5.4 % in Table 2 and −5.7 % in Table 3. This reduction means that the "Income" levels between the treated and control groups have become much closer to each other after matching.

The p-values for all covariates after matching are greater than 0.05, indicating that there are no statistically significant differences between the treated and control groups, which is desirable. Likewise, the ratio of variances (V(T)/V(C)) is within the acceptable range for all covariates, suggesting that matching has also balanced the variability between groups. The analysis suggests PSM has been effective in balancing the covariates between the treated and untreated groups. This is crucial to reduce bias in the estimation of the effect of living in a village where extreme weather events have occurred, ensuring that observed differences in outcomes between groups are not due to differences in these covariates.

4.2. *Perceived severity*

Fig. 4 compares ATEs and ATETs of farmers living in villages where landslides and droughts have been experienced. Regarding the ATEs, it can be seen that landslides are only significant in one perception in both matching methods, the severity of climate change on natural resources. However, it has a negative sign (−0.34 with nearest neighbor and −0.38 with caliper). This implies that living in a village where three or more landslides have been experienced reduces farmers' perception that climate change negatively affects

Table 2
Balance of Covariates for Landslide PSM.

Variables	Unmatched Matched	Mean			%reduct |bias|	*t*-test		V(T)/V(C)
		Treated	Control	%bias		t	p > t	
Less than 60 years	U	0.63333	0.64583	−2.6		−0.23	0.816	
	M	0.62712	0.58475	8.7	−239.0	0.66	0.507	
Female	U	0.49167	0.47917	2.5		0.22	0.824	
	M	0.49153	0.51695	−5.1	−103.4	−0.39	0.698	
Marital status	U	0.20000	0.18750	3.2		0.28	0.777	
	M	0.19492	0.16949	6.4	−103.4	0.5	0.615	
Education	U	0.38333	0.39167	−1.7		−0.15	0.879	
	M	0.38983	0.35593	6.9	−306.8	0.54	0.592	
Income	U	0.69167	0.63750	11.5		1.02	0.309	
	M	0.68644	0.71186	−5.4	53.1	−0.42	0.672	
Workers	U	2.7667	3.0250	−8.4		−0.69	0.491	0.29*
	M	2.7797	2.8644	−2.8	67.2	−0.26	0.797	0.50*
Farm Size	U	0.70833	0.74583	−8.4		−0.76	0.450	
	M	0.71186	0.70339	1.9	77.4	0.14	0.887	
Water	U	0.70833	0.63750	15.1		1.34	0.182	
	M	0.70339	0.70339	0.0	100.0	0.00	1.000	
Forest	U	0.65833	0.65417	0.9		0.08	0.938	
	M	0.66949	0.67797	−1.8	−103.4	−0.14	0.890	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
B Statistic < 16.1 %.
Balancing property satisfied: YES.
Common support imposed: YES.
Source: Authors.

Table 3
Balance of Covariates for Drought PSM.

Variables	Unmatched Matched	Mean			%reduct |bias|	*t*-test		V(T)/V(C)
		Treated	Control	%bias		t	p > t	
Less than 60 years	U	0.65833	0.63333	5.2		0.47	0.642	
	M	0.66372	0.65487	1.8	64.6	0.14	0.889	
Female	U	0.45000	0.50000	−10.0		−0.89	0.372	
	M	0.46903	0.47788	−1.8	82.3	−0.13	0.895	
Marital status	U	0.19167	0.19167	0.0		0.00	1.000	
	M	0.19469	0.19469	0.0	.	0.00	1.000	
Education	U	0.35833	0.40417	−9.4		−0.84	0.402	
	M	0.37168	0.35398	3.6	61.4	0.28	0.783	
Income	U	0.72500	0.62083	22.3		1.97	0.050	
	M	0.70496	0.73451	−5.7	74.5	−0.44	0.658	
Workers	U	3.20000	2.80830	10.9		1.05	0.297	2.23*
	M	2.86730	2.70800	4.4	59.3	0.42	0.671	0.71
Farm Size	U	0.72500	0.73750	−2.8		−0.25	0.801	
	M	0.73451	0.77876	−10.0	254.0	0.77	0.441	
Water	U	0.69167	0.64583	9.7		0.86	0.388	
	M	0.68142	0.69912	−3.8	61.4	−0.29	0.775	
Forest	U	0.57500	0.69583	−25.2		−2.28	0.023	
	M	0.59292	0.60177	−1.8	92.7	−0.14	0.893	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
B Statistic: 14.6%.
Balancing property satisfied: YES.
Common support imposed: YES.
Source: Authors.

natural resources compared to farmers living in villages where landslides have not been experienced. Moreover, landslide was also significant in the severity of climate change in other farmers, but only in one matching technique (−0.27 with caliper). This suggests that exposure to landslides may lead some farmers to downplay the severity of climate change impacts on others.

Regarding droughts, residing in villages that have experienced two or more droughts shows a positive and significant effect on how farmers perceive the severity of the impacts of climate change, particularly on the village's natural resources and the other farmers. The ATEs on the perceived severity of natural resources are 0.39 using nearest neighbor matching and 0.34 using caliper matching, both statistically significant at the 5 % level. Similarly, the effects on farmers within the village show ATEs of 0.30 (nearest neighbor) at the 10 % level and 0.31 (caliper), significant at the 5 % level. These findings suggest that farmers residing in villages affected by droughts perceived a higher severity of climate change, compared to farmers living in villages where droughts have not been reported.

On the other hand, the ATETs reflect the average treatment effect among only the treated group. For landslides, none of the ATETs are statistically significant, indicating that living directly in a village where three or more landslides have occurred since 2005 does not significantly influence any of the categories of farmers' perceived severity. In contrast, droughts exhibit positive and statistically significant effects among the treated farmers. The ATETs on the perceived severity of natural resources is 0.38 using nearest neighbor matching and 0.42 using caliper matching, both statistically significant at the 5 % level. Similarly, the effects on farmers within the village show ATETs of 0.40 (nearest neighbor) and 0.42 (caliper), also significant at the 5 % level. These findings suggest that farmers' perceptions of severity increase due to their direct experience with droughts in comparison with farmers who live in villages where droughts have not been reported.

4.3. Perceived vulnerability

In terms of perceived vulnerability (Fig. 5), landslides show no statistically significant effects in any of the categories, neither in the ATEs nor in the ATETs. This indicates that living in a village where three or more landslides have occurred since 2005 does not significantly influence farmers' perceptions of their vulnerability to climate change. In contrast, droughts have positive and significant effects in all three categories analyzed for both ATEs and ATETs.

The first category indicates that living in a drought-affected village significantly increases how frequently farmers worry about climate change on a weekly basis. In this case, the ATEs are positive and significant at the 1 % level, with values of 0.47 using nearest neighbor matching and 0.44 using caliper matching. Likewise, the second category indicates how often farmers worry about being negatively impacted by climate change. Here, the ATEs are 0.53 (nearest neighbor) and 0.47 (caliper), both also significant at the 1 %

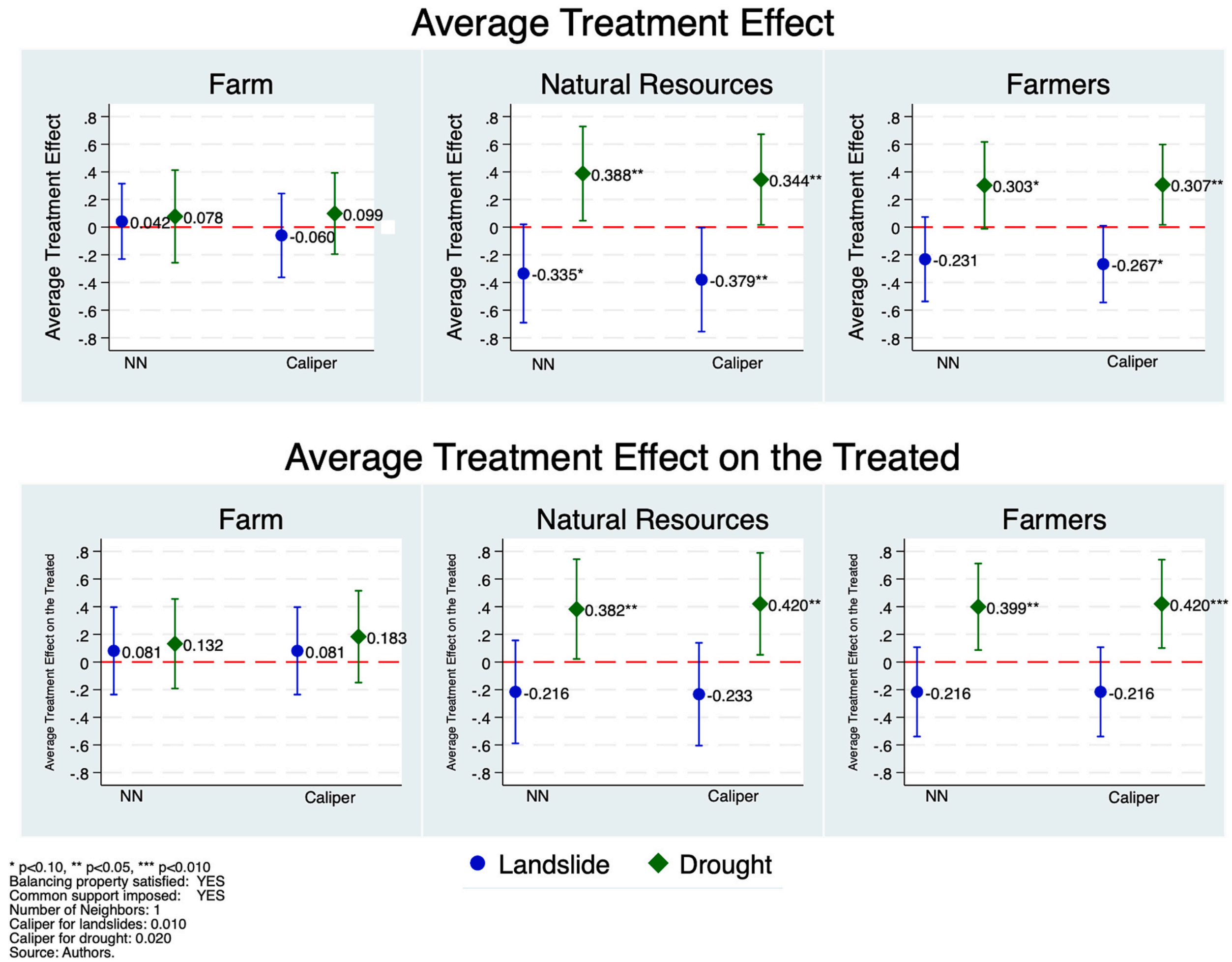

Fig. 4. Estimated ATEs and ATETs for Perceived Severity.

level. Lastly, the third category measures the concerns about the effects of climate change on their farming activities. In this case, the ATEs are 0.43 (nearest neighbor) and 0.31 (caliper), statistically significant at the 5 % and 10 % levels, respectively. These findings suggest that farmers who have experienced droughts exhibit higher perceptions of vulnerability to climate change. They worry more frequently about the potential adverse impacts on their livelihoods, in contrast to farmers residing in villages unaffected by droughts.

Regarding the ATETs, the analysis reveals that for the first category of perceived vulnerability, the effects are positive and significant at the 1 % level, with values of 0.61 using nearest neighbor matching and 0.59 using caliper matching. Similarly, the treatment effects are larger and remain positive for how often farmers worry about being negatively impacted by climate change, with ATETs of 0.70 (nearest neighbor) and 0.65 (caliper), both also significant at the 1 % level. Regarding concerns about the effects of climate change on their farming activities, drought experiences yield positive ATETs of 0.53 (nearest neighbor) and 0.54 (caliper), both statistically significant at the 5 % level. Overall, these findings imply that experiencing droughts substantially increases the perceived vulnerability among farmers, leading them to worry more frequently about climate change and its potential adverse effects on their livelihoods in comparison to farmers who live in villages where droughts have not been experienced.

4.4. Psychological distance

For the psychological distance, living in a village where three or more landslides have occurred is associated with only one statistically significant ATE (Fig. 6), specifically for hypothetical distance 2 (I am not sure that climate change is really happening). This effect is positive and significant at the 5 % level, with estimates of 0.38 using nearest neighbor and 0.32 with caliper. Also, it can be observed that the sign is positive, implying that farmers in these villages are not sure that climate change is happening, compared to farmers in villages where landslides have not been experienced. This may explain why none of the other perceptions are statistically significant.

In comparison, droughts have statistically significant effects in three categories using both matching methods. The first category is Temporal 2 (The effects of climate change are going to happen in the future, but they are NOT happening right now), where the ATEs

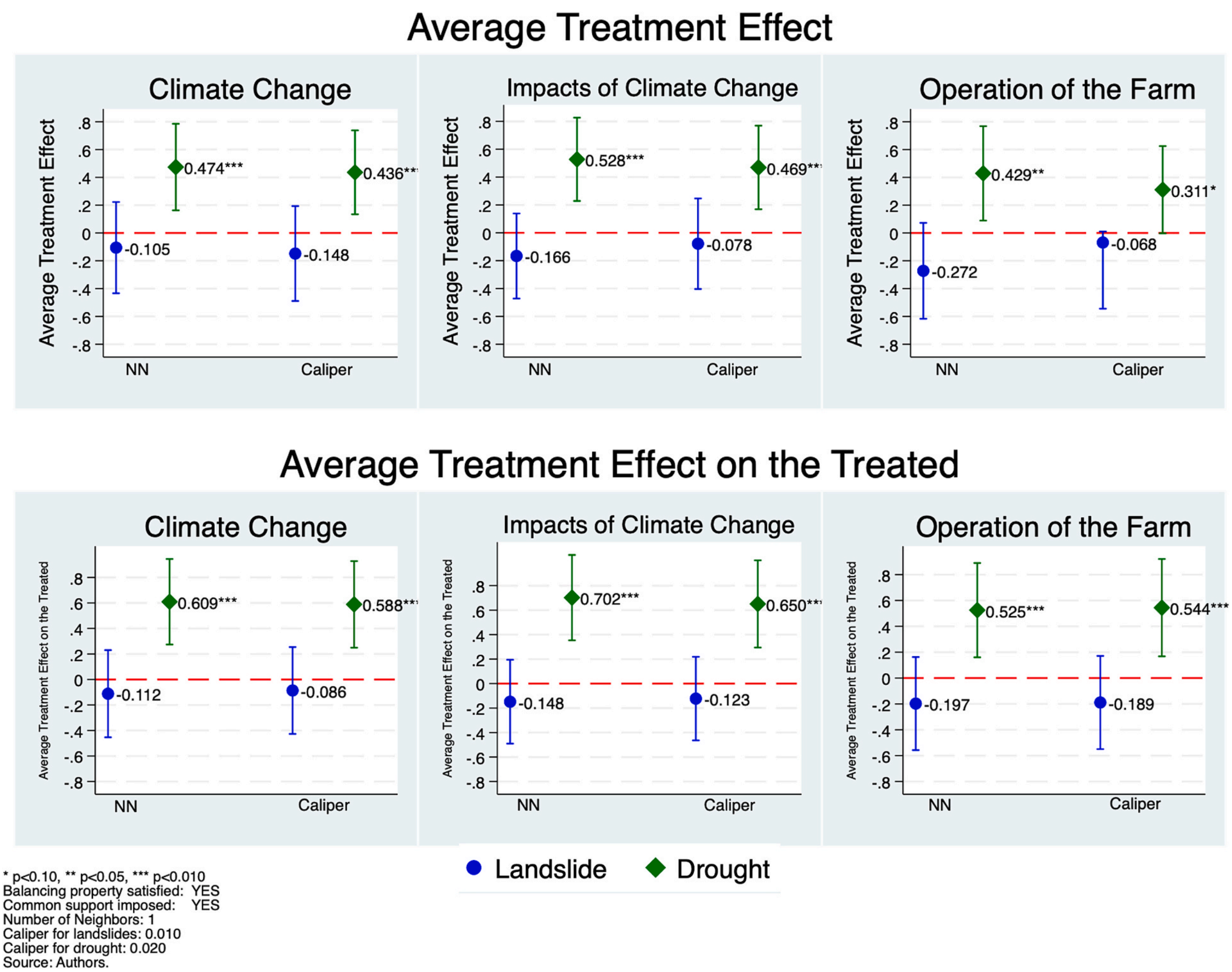

Fig. 5. Estimated ATEs and ATETs for Perceived Vulnerability.

are −0.38 (nearest neighbor) and −0.39 (caliper), significant at the 5 % and 10 % levels, respectively. This shows that living in a village affected by drought reduces farmers' psychological distance, making them perceive the effects of climate change as more immediate. The second category is hypothetical 2 (I am not sure that climate change is really happening). Unlike the landslide's ATEs, the drought showed significant negative ATEs of − 0.36 (nearest neighbor), significant at the 5 % level, and − 0.25 (caliper), significant at the 10 % level. Finally, the third category is hypothetical 4 (Droughts are a consequence of climate change), where the ATEs are positive at 0.34 (nearest neighbor) and 0.40 (caliper), both significant at the 5 % and 1 % levels, respectively. Additionally, there were two other categories where droughts showed statistically significant ATEs, but only with one matching method. For the category Social 2 (Climate change is going to affect other farmers but NOT me), the ATE with the caliper was −0.19 and significant at the 5 % level. Lastly, in the category Hypothetical 1 (Climate change is already affecting me), the ATE was 0.28 using the nearest neighbor matching method, which is significant at the 10 % level.

Fig. 7 *shows* the results from the ATET estimations. As can be seen, landslides do not have a significant impact on any of the categories studied of psychological distance. However, droughts do have significant effects in certain categories. Regarding spatial distance, neither type of event shows significant effects, indicating that experiencing these events does not significantly alter the perception of how close farmers perceive the effects of climate change in a geographical dimension. Regarding temporal distance, the first category presents the effects of climate change as an event closer in time. Here, drought has positive ATETs of 0.29 (nearest neighbor) and 0.37 (caliper), significant at the 10 % and 5 % levels, respectively. Similarly, the second category reflects the perception of climate change as a distant event in time. In this case, drought has negative ATETs of −0.44 (nearest neighbor) and −0.48 (caliper), significant at the 1 % and 10 % level, respectively. This indicates that living in a village that has experienced drought reduces the psychological distance of farmers, making them feel that the effects of climate change are less distant. Both categories suggest that these farmers perceive the impacts of climate change as more immediate on a temporal scale in comparison to farmers who live in villages with no drought experience.

In the social dimension, the first category shows positive ATETs of 0.22 (nearest neighbor) and 0.25 (caliper), both significant at the 10 % level. This category reflects the perception of climate change impacts as being closer to farmers who are similar to them. As a

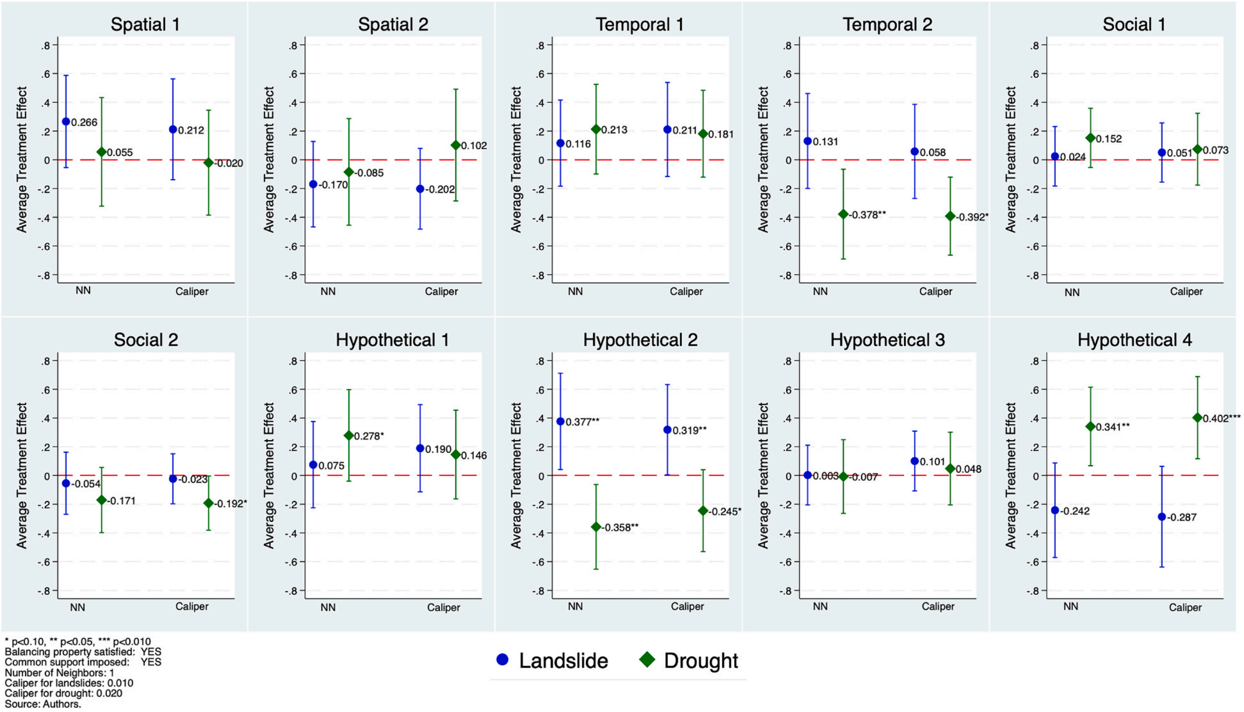

Fig. 6. Estimated ATEs for Psychological Distance.

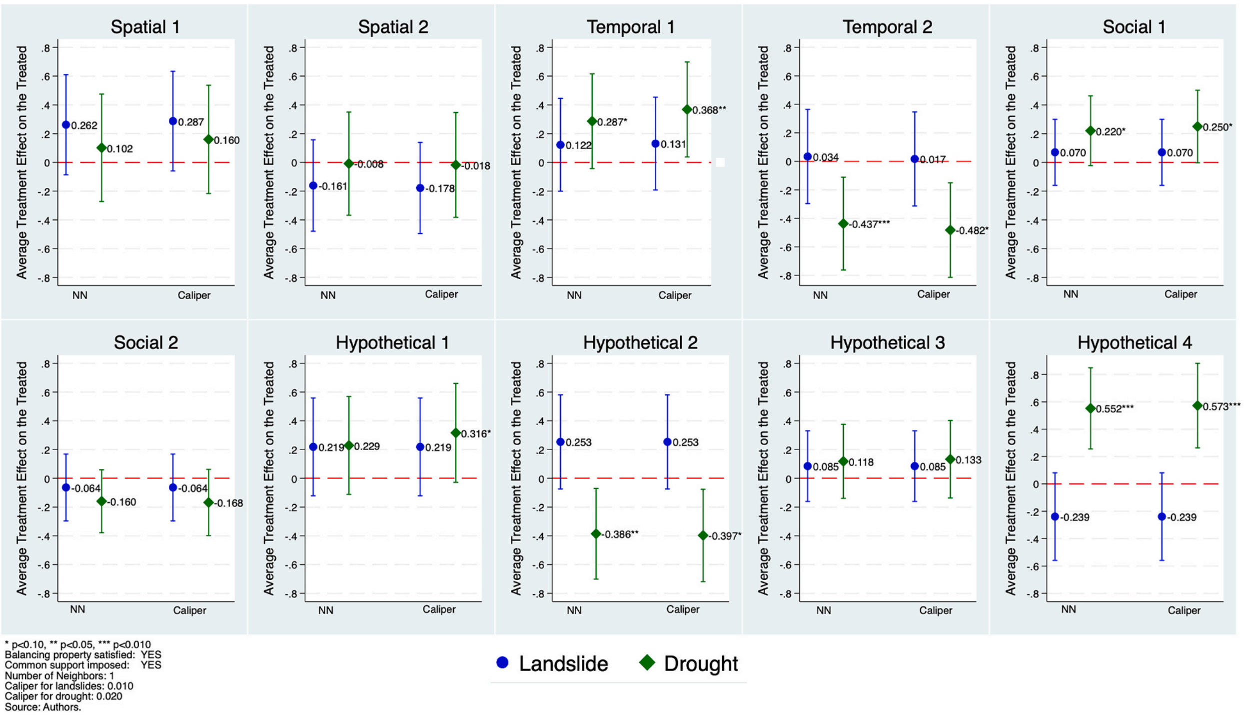

Fig. 7. Estimated ATETs for Psychological Distance.

result, farmers living in villages that have experienced drought perceive the effects of climate change as socially closer compared to those in villages where droughts have not occurred. However, the second category, which considers the effects of climate change from a more distant social perspective, is not significant. Additionally, in the hypothetical distances, only one perception, hypothetical distance 1, which frames climate change as an event already affecting farmers, was statistically significant, with only one matching technique (0.32 with caliper).

Moreover, the hypothetical distances two and four were significant in the two matching techniques. The second category frames climate change as a distant event with uncertain occurrence. In this case, droughts result in negative ATETs of − 0.39 (nearest neighbor) and − 0.40 (caliper), both significant at the 5 % level. This suggests that the experience of droughts reduces the perception of uncertainty about the occurrence of climate change, compared to villages where droughts have not occurred. The fourth category directly links droughts as a consequence of climate change. Here, the ATETs are positive at 0.55 (nearest neighbor) and 0.57 (caliper), both significant at the 1 % level, indicating that living in villages that have experienced droughts significantly increases the perception that these events are indeed a consequence of climate change compared to farmers in villages where droughts have not been experienced. A summary of all ATEs and ATETS can be found in Appendix A1**.**

4.5. Robustness check

To assess the robustness of our results against potential hidden biases, we calculated Rosenbaum bounds for the perception variables studied. Rosenbaum bounds are a sensitivity analysis method used in observational studies to assess the robustness of causal inference results to potential hidden biases from unobserved variables. They introduce a parameter, Gamma (Γ), which quantifies how much an unobserved variable would need to influence the odds of treatment assignment to alter the study's conclusions. For example, if $\Gamma = 1.5$, it implies that two individuals with the same observed characteristics could have up to a 50 % difference in their likelihood of receiving the treatment due to unobserved factors. By calculating Rosenbaum bounds across different values of Γ, researchers can determine how sensitive their findings are to hidden bias: if large Γ values are needed to make the effect insignificant, the results are considered robust; if small values suffice, the findings are more vulnerable to unobserved confounders.

To evaluate the potential influence of unobserved factors, we examined varying levels of gamma (Γ). We found no hidden biases ($\Gamma = 1$), as well as cases where the probability increased by 50 % ($\Gamma = 1.5$) and 100 % ($\Gamma = 2$). These results were estimated using the two matching methods previously employed: nearest neighbor and caliper. Appendix A2. shows the results of the Rosenbaum Bounds in the case of living in villages where landslides have been experienced. None of the previously estimated ATETs was significant, and when analyzing the results for Gamma 1, 1.5, and 2, no significant treatment effects were found for any of the variables, indicating that even in the presence of unobserved factors, the ATETs would still be non-significant. This suggests that living in a village where three or more landslides have occurred since 2005, does not have a statistically significant impact on the variables included for perceived severity, perceived vulnerability, and psychological distance and that this conclusion is robust to possible unobserved biases.

In Appendix A3., the results of the Rosenbaum bounds for the drought treatment are presented. For Perceived Severity, both "Natural Resources" and "Farmers" show significant ATETs at the 5 % level. The Rosenbaum bounds at Gamma level 1 remain significant at the 5 % and 1 % levels, respectively. At higher Gamma levels ($\Gamma = 1.5$ and $\Gamma = 2$), both effects remain significant at the 1 % level but only at the lower bound. This suggests that the effect is robust to biases that reduce the positive impact of drought on these perceptions but may be overestimated. Regarding Perceived Vulnerability, all three ATETs studied were significant. The Rosenbaum bounds analysis shows that the ATETs of "Climate Change" and "Climate Change Impacts" remain significant at Gamma levels of 1 and 1.5, indicating robustness to low unobserved biases. However, at Gamma 2, the effects are only significant at the lower bound, suggesting that they remain significant under moderate bias but could be overestimated. As for the variable "Operation of the Farm", it remains significant at Gamma = 1 but is only significant at the lower bound for the other two levels ($\Gamma = 1.5$ and $\Gamma = 2$), indicating the possibility of overestimation while maintaining significance.

For the psychological distance variables, the ATETs for "Temporal Distance 1" and "Hypothetical Distance 1" are significant at the 5 % level and negative. The Rosenbaum bounds show that both are significant in the absence of unobserved biases ($\Gamma = 1$). However, they are only significant at the upper bound when Gamma increases ($\Gamma = 1.5$ and $\Gamma = 2$), implying the effect is robust to biases that increase the negative effect, potentially overestimating it. For "Temporal distance 2" and "Social distance 1", the ATETs are significant and positive. Analyzing the bounds, we find that they are significant at 5 % when no unobserved biases are present ($\Gamma = 1$). However, at the higher levels ($\Gamma = 1.5$, and $\Gamma = 2$), they are only significant at the lower bound, suggesting robustness but with a risk of overestimation. Finally, for "Hypothetical Distance 4", the ATET is positive and significant at the 1 % level, with Rosenbaum bounds remaining significant across all Gamma levels tested. This suggests that, even in the presence of unobserved biases, living in a village affected by droughts maintains a significant effect on the farmers' perception that these events are a consequence of climate change.

5. Discussion

The motivation behind this study was to investigate how farmers' experiences with extreme weather events influence their perceptions of climate change, as understanding these perceptions is crucial for designing effective climate adaptation strategies. Farmers' beliefs about climate change can significantly affect their willingness to adopt adaptive practices, influence their responses to policy interventions, and shape broader community resilience. Our research was conducted in central Colombia, with fieldwork carried out between 2022 and 2023. This region has been subject to recurring landslides and droughts, which are expected to increase as a result of climate change (IPCC, 2014). We used the conceptual frameworks of PMT and psychological distance to analyze, from various dimensions, how these environmental events shape farmers' perspectives on climate change.

From a methodological perspective, we employed PSM to compare farmers residing in villages affected by landslides and droughts with those who had not experienced these events. This matching approach was essential to mitigate selection bias and ensure that the treated and control groups were comparable on various socio-economic and farm-level covariates (Ali & Erenstein, 2017; Bonfrer et al., 2016; Bravo-Ureta et al., 2012; Ham et al., 2011). Using both nearest-neighbor and caliper matching helped to improve the balance between groups further and increase the robustness of the results (Austin, 2009; Dehejia & Wahba, 2002; Jacovidis et al., 2017). This matching approach allowed us to analyze the impact of these environmental events on farmers' perceptions of climate change while accounting for potential confounding factors.

The results of the ATETs indicated no statistically significant differences in the 16 perceptions assessed for farmers who experienced landslides, suggesting that landslides may not influence how farmers perceive the threat of climate change or how psychologically distant they feel themselves from its impacts. However, we found two statistically significant ATEs, suggesting that living in a village that has experienced landslides reduces farmers' perceived severity of climate impacts on natural resources and increases the hypothetical distance, suggesting that farmers may be less certain about the reality of climate change. This uncertainty may explain why no ATETs were statistically significant for landslide experiences. In some cases, it has been found that landslides may not significantly impact farmers' behavior related to climate change. Some studies support this; for instance, there is no evidence that an increased risk of landslide exposure leads farmers to be more willing to avoid or mitigate the impacts of landslides (Lin et al., 2008; Mertens et al., 2018; Spegel & Ek, 2022). This is mainly because, in most cases, landslides do not directly impact farmers' production, unless they occur directly on a farmer's property. In our case, we focus on farmers who experienced landslides affecting their production or the village's natural resources. However, the impact tends to be more indirect, often affecting road networks rather than farming activities themselves. Consequently, vulnerability is often more extensive and determined by the state of the transport network rather than the landslide event itself (Vranken et al., 2013; Winter et al., 2019).

Additionally, the regional context of the study area must be considered. In this particular region of Colombia, landslides frequently result from heavy rainfall (Aristizábal & Sánchez, 2020; Garcia-Delgado et al., 2022). Therefore, farmers' perceptions of changes in precipitation patterns are particularly relevant to the analysis. When comparing farmers' perceptions with observed climate data, research has found that their perceptions of rainfall often do not align with actual changes in the rainfall patterns (Dhanya & Ramachandran, 2016; Guido et al., 2020; Li et al., 2022; Mahony & Cannon, 2018; Simelton et al., 2013). This mismatch between experiential and empirical evidence could help explain why landslides, which are directly linked to precipitation, do not significantly influence farmers' perceptions of climate change.

On the other hand, with their prolonged nature and direct impact on agricultural productivity, droughts seem to heighten farmers' awareness of climate change risks. Empirical evidence supports farmers' perceptions of drought are well-grounded and accurate (Marin, 2010; Slegers, 2008; West et al., 2008). Furthermore, these perceptions shape their views on the risks posed by climate change (Carlton et al., 2016; Diggs, 1991; Konisky et al., 2016; Lyons et al., 2018; Panda, 2016; Saleh Safi et al., 2012). Consequently, we found statistically significant differences in 10 out of the 16 perceptions studied among farmers in drought-affected areas, suggesting they view climate change as more severe, perceive themselves as more vulnerable, and experience a closer psychological distance to its impacts.

In analyzing the application of the PMT, our findings support existing literature suggesting that drought shapes threat appraisal (Truelove et al., 2015). This cognitive process involves how individuals assess threats based on their perceived vulnerability and severity (Keshavarz & Karami, 2016). Under drought conditions, farmers' perceptions become particularly critical, reinforcing the notion that specific extreme weather events can directly shape their understanding of climate change risks (Keshavarz & Karami, 2016; Neisi et al., 2020). Our study found all dimensions of perceived vulnerability to be significant, highlighting that farmers not only recognize the severity of drought but also increasingly feel susceptible to its impacts. This is consistent with prior research emphasizing the role of perceived vulnerability in the context of drought, suggesting that farmers' awareness of drought-related risks plays a crucial role in determining their responses to climate threats (Delfiyan et al., 2021; Gebrehiwot & van der Veen, 2015; Scarpa & Thiene, 2011; van Duinen et al., 2015).

Regarding psychological distance, the results further support the idea that drought's perceived immediacy and relevance are shaped by multiple factors. The significance of both temporal distance dimensions (The effects of climate change are happening right now or in the future) and hypothetical distance 1 (Uncertainty about climate change) represent the effect of drought in determining the perception of the immediacy of climate change. Lower temporal distances of climate change usually lead to higher perceived relevance of the event (Kim et al., 2019). Additionally, the significance of hypothetical distance 4 (Droughts are a consequence of climate change) aligns with previous research showing that people often link drought to climate change, thereby increasing their sense of risk (Deng et al., 2017; Guillard et al., 2021). The high percentage of farmers (66.1 %) with direct access to water sources, such as a spring, river, or stream (Table 1), likely reduces their perception of drought risk, as they may feel more secure in their water availability compared to farmers without such access. This sense of security can diminish the perceived relevance of spatial and social distances, as farmers with immediate water resources might not feel as affected by or concerned with broader geographical variations in drought risk or social proximity to others impacted by drought. Consequently, their access to water could lessen the significance of spatial and social factors in shaping their perceptions of climate risks, making these distances less influential in the analysis (Becker & Sparks, 2020; Craig et al., 2019).

Farmers within the same region can have different, sometimes even opposite, perceptions of climate risks because individual experiences, resources, and attitudes shape how they interpret environmental threats. Factors like access to water, past experiences with drought, and personal knowledge about climate can lead farmers to view similar conditions differently. For example, one farmer with reliable irrigation may feel less threatened by drought than another nearby farmer relying solely on rainfall. Additionally, social influences, such as community discussions or access to information, can further affect individual perceptions. This variability means that even within a shared geographic area, farmers might assess climate risks in diverse ways, reflecting a range of personal and contextual factors that influence their interpretations of climate change (Parsons & Nielsen, 2021; Yazdanpanah et al., 2023).

Overall, the Rosenbaum bounds results suggest that perceptions of severity and vulnerability to extreme events such as droughts exhibit robust effects in the face of low to moderate unobserved biases. However, in some cases, especially in the psychological distance analysis, the effects may be overestimated under a higher level of bias ($\Gamma = 2$). Despite this, the ATETs maintain their significance in most cases, suggesting that living in drought-affected villages significantly influences farmers' perceptions of climate change and its consequences.

Our findings provide only partial support for the first hypothesis (H1), which proposed a significant difference in perceptions between farmers residing in villages affected by extreme weather events and those in unaffected villages. While landslides did not appear to influence farmers' perceptions, droughts clearly did, suggesting that the type of extreme event plays a crucial role in shaping farmers' views on climate change. Regarding the second hypothesis (H2), which suggested no difference in perceptions between farmers residing in villages affected by landslides and those affected by droughts, our results lead us to reject this hypothesis. The clear contrast between the two groups—significant differences in perceptions among farmers in drought-affected areas but none among those in landslide-affected areas— indicates that the type of extreme weather event significantly influences how farmers perceive climate change.

These findings underscore the importance of considering the nature and directness of the extreme weather events when evaluating their influence on climate change perceptions. Droughts, due to their gradual onset and prolonged impact on agricultural productivity, directly interfere with farmers' livelihoods, making the consequences of climate change more tangible and salient. This direct connection helps explain why farmers affected by droughts exhibit significantly higher perceived severity and vulnerability, and experience reduced psychological distance from climate change. In contrast, landslides often result in more localized, short-term disruptions, frequently affecting infrastructure rather than agricultural output. This more indirect impact, combined with their frequent occurrence in the region and potential normalization, may reduce their salience as climate change indicators in farmers' minds. These contextual and experiential factors help justify the differentiated perceptual responses observed in our analysis and support the idea that farmers' lived experiences are critical in shaping how they internalize and react to climate risks.

6. Conclusions

This study sheds light on how extreme weather experiences, particularly droughts and landslides, shape climate change perceptions among farmers in central Colombia. Using PMT and psychological distance as frameworks, we found that while droughts increased farmers' awareness and influenced their assessments of climate risk severity and vulnerability, landslides did not have a significant effect. PSM helped control for confounding factors, enhancing the accuracy of our comparisons between affected and unaffected villages.

However, this study has limitations. First, the reliance on self-reported perceptions may introduce cognitive biases, such as over- or underestimation of risks, which are common in behavioral studies. Second, although the PSM approach is useful, it may not fully account for unobserved factors influencing farmers' beliefs. Third, to achieve covariate balance in the matching procedure, age and education had to be simplified into binary indicators. Age was coded using a 60-year threshold, and education was transformed into a dummy variable indicating whether respondents had primary education as their highest level attained, the most common educational level in our sample. While these decisions improved the performance of the matching diagnostics, they may also limit the ability to capture more nuanced differences across the population. Finally, the focus on central Colombia provides valuable context-specific insights but may limit the generalizability of the findings to other regions, where environmental, institutional, or cultural conditions may differ. Future research could incorporate longitudinal data and qualitative methods to better understand how farmers' experiences and perceptions evolve over time. From a policy perspective, it might be useful to implement targeted communication strategies. Leveraging local experiences and climate data can encourage more proactive adaptation behaviors, while training programs focused on sustainable agricultural practices can help farmers build resilience, especially in drought-affected regions.

CRediT authorship contribution statement

Alexander Cano: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Bente Castro-Campos:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Funding

This research has received financial support from the German Academic Exchange Service through the Development-Related Postgraduate Courses program under contract number P1401273; and from the program "*Inclusión productiva y social: programas y políticas para la promoción de una economía formal*,'' code 60185, which is part of the *Alianza EFI* under the Contingent Recovery Agreement No. FP44842-220–2018.

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.

Appendix A.1. Summary of results

Perceptions	Average Treatment Effect				Average Treatment Effect on the Treated			
	Landslide			Landslide	Landslide			Landslide
	NN	Caliper	NN	Caliper	NN	Caliper	NN	Caliper
Perceived Severity								
Farm	0.042	−0.06	0.042	0.042	0.081	0.08	0.132	0.183
Natural Resources	−0.335*	−0.379**	−0.335*	−0.335*	−0.216	−0.233	0.382**	0.420**
Farmers	−0.231	−0.267*	−0.231	−0.231	−0.216	−0.216	0.399**	0.420**
Perceived Vulnerability								
Climate change	−0.105	−0.148	−0.105	−0.105	−0.112	−0.086	0.609***	0.588***
Impacts of climate change	−0.166	−0.078	−0.166	−0.166	−0.148	−0.123	0.702***	0.650***
Operation of the farm	−0.272	−0.068	−0.272	−0.272	−0.197	−0.189	0.525**	0.544**
Psychological Distance								
Spatial 1	0.266	0.212	0.266	0.266	0.262	0.287	0.102	0.16
Temporal 1	0.116	0.211	0.116	0.116	0.122	0.131	0.287*	0.368**
Social 1	0.024	0.051	0.024	0.024	0.07	0.07	0.220*	0.250*
Hypothetical 1	0.075	0.19	0.075	0.075	0.219	0.219	0.229	0.316*
Hypothetical 3	0.003	0.101	0.003	0.003	0.085	0.085	0.118	0.133
Hypothetical 4	−0.242	−0.287	−0.242	−0.242	−0.239	−0.239	0.552***	0.573***
Spatial 2	−0.17	−0.202	−0.17	−0.17	−0.161	−0.178	−0.009	−0.018
Temporal 2	0.131	0.058	0.131	0.131	0.034	0.016	−0.437**	−0.482**
Social 2	−0.054	−0.023	−0.054	−0.054	−0.064	−0.064	−0.16	−0.168
Hypothetical 2	0.377**	0.319**	0.377**	0.377**	0.253	0.253	−0.386**	−0.397**
N	360	360	360	360	360	360	360	360

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
Balancing property satisfied: YES.
Common support imposed: YES.
Number of Neighbors: 1.
Caliper for landslides: 0.010.
Caliper for drought: 0.020Source: Authors.

Appendix A.2. Rosenbaum bounds for ATET — landslides

Variables	Rosenbaum Bounds												
	Gamma (Γ)	Nearest Neighbor						Caliper					
		sig+	sig-	t-hat+	t-hat-	CI+	CI-	sig+	sig-	t-hat+	t-hat-	CI+	CI-
Perceived Severity													
Farm	1	0.3882	0.3882	0.0000	0.0000	−0.2500	0.5000	0.3882	0.3882	0.0000	0.0000	−0.2500	0.5000
	1.5	0.9290	0.0203	−0.2500	0.5000	−0.5000	0.5000	0.9290	0.0203	−0.2500	0.5000	−0.5000	0.5000
	2	0.9970	0.0004	−0.5000	0.5000	−0.5000	1.0000	0.9970	0.0004	−0.5000	0.5000	−0.5000	1.0000
Natural Resources	1	0.0642	0.0642	−0.2500	−0.2500	−0.5000	0.0000	0.0604	0.0604	−0.2500	−0.2500	−0.5000	0.0000
	1.5	0.0004	0.5967	−0.5000	0.0000	−1.0000	0.5000	0.0004	0.5842	−0.5000	0.0000	−1.0000	0.5000
	2	0.0000	0.9330	−1.0000	0.2500	−1.0000	0.7500	0.0000	0.9286	−1.0000	0.2500	−1.0000	0.7500
Farmers	1	0.0455	0.0455	0.0000	0.0000	−0.5000	0.0000	0.0499	0.0499	0.0000	0.0000	−0.5000	0.0000
	1.5	0.0003	0.4928	−0.5000	0.0000	−1.0000	0.5000	0.0004	0.5069	−0.5000	0.0000	−1.0000	0.5000
	2	0.0000	0.8777	−1.0000	0.0000	−1.0000	0.5000	0.0000	0.8837	−1.0000	0.0000	−1.0000	0.5000
Perceived Vulnerability													
Climate change	1	0.4301	0.4301	0.0000	0.0000	−0.5000	0.2500	0.4637	0.4637	0.0000	0.0000	−0.5000	0.2500
	1.5	0.0281	0.9395	−0.5000	0.2500	−1.0000	0.5000	0.0356	0.9473	−0.2500	0.2500	−0.7500	0.5000
	2	0.0007	0.9975	−0.5000	0.5000	−1.0000	1.0000	0.0011	0.9979	−0.5000	0.5000	−1.0000	1.0000
Impacts of climate change	1	0.2900	0.2900	0.0000	0.0000	−0.5000	0.0000	0.3418	0.3418	0.0000	0.0000	−0.5000	0.0000
	1.5	0.0133	0.8618	−0.5000	0.0000	−0.5000	0.5000	0.0197	0.8901	−0.2500	0.0000	−0.5000	0.5000
	2	0.0003	0.9886	−0.5000	0.5000	−1.0000	1.0000	0.0005	0.9921	−0.5000	0.5000	−1.0000	1.0000
Operation of the farm	1	0.2825	0.2825	0.0000	0.0000	−0.5000	0.0000	0.3144	0.3144	0.0000	0.0000	−0.5000	0.0000
	1.5	0.0119	0.8610	−0.5000	0.0000	−1.0000	0.5000	0.0156	0.8787	−0.5000	0.0000	−1.0000	0.5000
	2	0.0002	0.9889	−0.5000	0.5000	−1.4000	0.7500	0.0003	0.9910	−0.5000	0.5000	−1.2500	0.7500
Psychological Distance													
Spatial Distance 1	1	0.1700	0.1700	0.0000	0.0000	0.0000	0.0000	0.1289	0.1289	0.0000	0.0000	0.0000	0.0000
	1.5	0.0088	0.6651	0.0000	0.0000	−0.5000	0.0000	0.0060	0.5803	0.0000	0.0000	−0.5000	0.0000
	2	0.0003	0.9212	−0.5000	0.0000	−1.0000	0.5000	0.0002	0.8752	−0.5000	0.0000	−1.0000	0.5000
Temporal Distance 1	1	0.2451	0.2451	0.0000	0.0000	0.0000	0.0000	0.2370	0.2370	0.0000	0.0000	0.0000	0.0000
	1.5	0.7920	0.0132	0.0000	0.0000	−0.5000	1.0000	0.7770	0.0131	0.0000	0.0000	−0.5000	0.5000
	2	0.9711	0.0004	0.0000	0.5000	−0.5000	1.0000	0.9661	0.0004	0.0000	0.5000	−0.5000	1.0000

(*continued on next page*)

(*continued*)

Variables	Rosenbaum Bounds												
	Gamma (Γ)	Nearest Neighbor						Caliper					
		sig+	sig-	t-hat+	t-hat-	CI+	CI-	sig+	sig-	t-hat+	t-hat-	CI+	CI-
Social Distance 1	1	0.5611	0.5611	0.0000	0.0000	0.0000	0.0000	0.5611	0.5611	0.0000	0.0000	0.0000	0.0000
	1.5	0.9387	0.1093	0.0000	0.0000	−0.5000	0.2500	0.9387	0.1093	0.0000	0.0000	−0.5000	0.2500
	2	0.9948	0.0126	0.0000	0.0000	−0.5000	0.5000	0.9948	0.0126	0.0000	0.0000	−0.5000	0.5000
Hypothetical Distance 1	1	0.1747	0.1747	0.0000	0.0000	0.0000	0.2500	0.2229	0.2229	0.0000	0.0000	0.0000	0.0000
	1.5	0.7129	0.0067	0.0000	0.2500	−0.2500	1.0000	0.7624	0.0116	0.0000	0.0000	−0.2500	0.9000
	2	0.9490	0.0001	0.0000	0.6500	−0.5000	1.0000	0.9621	0.0003	0.0000	0.5000	−0.5000	1.0000
Spatial Distance 2	1	0.0653	0.0653	0.0000	0.0000	0.0000	0.5000	0.0443	0.0443	0.0000	0.0000	0.0000	0.5000
	1.5	0.5180	0.0009	0.0000	0.5000	−0.2500	1.0000	0.4269	0.0005	0.0000	0.5000	0.0000	1.0000
	2	0.8743	0.0000	0.0000	0.5000	−0.5000	1.0000	0.8118	0.0000	0.0000	0.5000	−0.5000	1.0000
Temporal Distance 2	1	0.3198	0.3198	0.0000	0.0000	0.0000	0.0000	0.3547	0.3547	0.0000	0.0000	0.0000	0.0000
	1.5	0.8508	0.0230	0.0000	0.0000	−0.5000	0.5000	0.8643	0.0314	0.0000	0.0000	−0.5000	0.5000
	2	0.9835	0.0009	0.0000	0.5000	−1.0000	1.0000	0.9849	0.0015	0.0000	0.2500	−1.0000	1.0000
Social Distance 2	1	0.3376	0.3376	0.0000	0.0000	0.0000	0.0000	0.3376	0.3376	0.0000	0.0000	0.0000	0.0000
	1.5	0.0534	0.7757	0.0000	0.0000	0.0000	0.0000	0.0534	0.7757	0.0000	0.0000	0.0000	0.0000
	2	0.0063	0.9461	0.0000	0.0000	−0.5000	0.0000	0.0063	0.9461	0.0000	0.0000	−0.5000	0.0000
Hypothetical Distance 2	1	0.0875	0.0875	0.0000	0.0000	0.0000	0.5000	0.0967	0.0967	0.0000	0.0000	0.0000	0.5000
	1.5	0.5767	0.0015	0.0000	0.5000	−0.5000	1.0000	0.5943	0.0019	0.0000	0.5000	−0.3000	1.0000
	2	0.9022	0.0000	0.0000	1.0000	−1.0000	1.0000	0.9087	0.0000	0.0000	1.0000	−0.7500	1.0000
Hypothetical Distance 3	1	0.2707	0.2707	0.0000	0.0000	0.0000	0.0000	0.2707	0.2707	0.0000	0.0000	0.0000	0.0000
	1.5	0.7731	0.0230	0.0000	0.0000	0.0000	0.5000	0.7731	0.0230	0.0000	0.0000	0.0000	0.5000
	2	0.9581	0.0012	0.0000	0.0000	−0.5000	0.5000	0.9581	0.0012	0.0000	0.0000	−0.5000	0.5000
Hypothetical Distance 4	1	0.0664	0.0664	0.0000	0.0000	−0.1000	0.0000	0.0664	0.0664	0.0000	0.0000	−0.1000	0.0000
	1.5	0.0014	0.4681	−0.1000	0.0000	−0.5000	0.0000	0.0014	0.4681	−0.1000	0.0000	−0.5000	0.0000
	2	0.0000	0.8223	−0.5000	0.0000	−1.0000	0.5000	0.0000	0.8223	−0.5000	0.0000	−1.0000	0.5000
N	118 matched pairs							118 matched pairs					

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
Number of Neighbors: 1.
Caliper for landslides: 0.010.
Caliper for drought: 0.020.
Source: Authors.

Appendix A.3. Rosenbaum bounds for ATET — droughts

Variables	Rosenbaum Bounds												
	Gamma (Γ)	Nearest Neighbor						Caliper					
		sig+	sig-	t-hat+	t-hat-	CI+	CI-	sig+	sig-	t-hat+	t-hat-	CI+	CI-
Perceived Severity													
Farm	1	0.2126	0.2126	0.0000	0.0000	0.0000	0.5000	0.1439	0.1439	0.0000	0.0000	0.0000	0.5000
	1.5	0.8135	0.0059	0.0000	0.5000	−0.5000	0.5000	0.7168	0.0030	0.0000	0.5000	−0.5000	1.0000
	2	0.9824	0.0001	−0.5000	0.5000	−0.7500	1.0000	0.9595	0.0000	−0.4000	0.5000	−0.7500	1.0000
Natural Resources	1	0.0130	0.0130	0.5000	0.5000	0.0000	1.0000	0.0103	0.0103	0.5000	0.5000	0.0000	1.0000
	1.5	0.3096	0.0000	0.0000	0.7500	−0.2500	1.0000	0.2612	0.0000	0.0000	1.0000	−0.2500	1.0000
	2	0.7621	0.0000	0.0000	1.0000	−0.5000	1.5000	0.7014	0.0000	0.0000	1.0000	−0.5000	1.5000
Farmers	1	0.0035	0.0035	0.5000	0.5000	0.0000	1.0000	0.0037	0.0037	0.5000	0.5000	0.0000	1.0000
	1.5	0.1545	0.0000	0.0000	1.0000	0.0000	1.0000	0.1492	0.0000	0.0000	1.0000	0.0000	1.0000
	2	0.5581	0.0000	0.0000	1.0000	−0.5000	1.0000	0.5359	0.0000	0.0000	1.0000	−0.5000	1.2500
Perceived Vulnerability													
Climate change	1	0.0006	0.0006	0.5000	0.5000	0.0000	1.0000	0.0010	0.0010	0.5000	0.5000	0.0000	1.0000
	1.5	0.0567	0.0000	0.0000	1.0000	0.0000	1.5000	0.0744	0.0000	0.0000	1.0000	0.0000	1.5000
	2	0.3302	0.0000	0.0000	1.0000	−0.5000	1.5000	0.3725	0.0000	0.0000	1.0000	−0.5000	1.5000
Impacts of climate change	1	0.0002	0.0002	0.5000	0.5000	0.0000	1.0000	0.0004	0.0004	0.5000	0.5000	0.0000	1.0000
	1.5	0.0301	0.0000	0.0000	1.0000	0.0000	1.5000	0.0391	0.0000	0.0000	1.0000	0.0000	1.5000
	2	0.2235	0.0000	0.0000	1.5000	0.0000	1.5000	0.2453	0.0000	0.0000	1.0000	0.0000	1.5000
Operation of the farm	1	0.0098	0.0098	0.5000	0.5000	0.0000	1.0000	0.0142	0.0142	0.5000	0.5000	0.0000	1.0000
	1.5	0.2801	0.0000	0.0000	1.0000	−0.5000	1.5000	0.3120	0.0000	0.0000	1.0000	−0.5000	1.5000
	2	0.7391	0.0000	0.0000	1.0000	−0.5000	1.5000	0.7583	0.0000	0.0000	1.2500	−0.5000	1.5000
Psychological Distance													
Spatial Distance 1	1	0.3218	0.3218	0.0000	0.0000	0.0000	0.0000	0.3057	0.3057	0.0000	0.0000	0.0000	0.0000
	1.5	0.0261	0.8405	0.0000	0.0000	−0.5000	0.5000	0.0267	0.8145	0.0000	0.0000	−0.5000	0.5000
	2	0.0012	0.9800	−0.5000	0.0000	−1.0000	1.0000	0.0014	0.9719	−0.5000	0.0000	−1.0000	1.0000
Temporal Distance 1	1	0.0306	0.0306	0.0000	0.0000	0.0000	0.5000	0.0142	0.0142	0.0000	0.0000	0.0000	0.5000

(*continued on next page*)

(*continued*)

Variables	Rosenbaum Bounds												
	Gamma (Γ)	Nearest Neighbor						Caliper					
		sig+	sig-	t-hat+	t-hat-	CI+	CI-	sig+	sig-	t-hat+	t-hat-	CI+	CI-
	1.5	0.3097	0.0004	0.0000	0.5000	0.0000	1.0000	0.1854	0.0002	0.0000	0.5000	0.0000	1.0000
	2	0.6785	0.0000	0.0000	0.5000	0.0000	1.0000	0.5000	0.0000	0.0000	1.0000	0.0000	1.0000
Social Distance 1	1	0.0154	0.0154	0.0000	0.0000	0.0000	0.1000	0.0139	0.0139	0.0000	0.0000	0.0000	0.5000
	1.5	0.2073	0.0002	0.0000	0.1000	0.0000	0.5000	0.1954	0.0001	0.0000	0.5000	0.0000	0.5000
	2	0.5452	0.0000	0.0000	0.5000	0.0000	1.0000	0.5271	0.0000	0.0000	0.5000	0.0000	1.0000
Hypothetical Distance 1	1	0.0680	0.0680	0.0000	0.0000	0.0000	0.5000	0.0281	0.0281	0.0000	0.0000	0.0000	0.5000
	1.5	0.5034	0.0011	0.0000	0.5000	0.0000	1.0000	0.3098	0.0003	0.0000	0.5000	0.0000	1.0000
	2	0.8575	0.0000	0.0000	0.7500	−0.5000	1.0000	0.6881	0.0000	0.0000	1.0000	−0.5000	1.5000
Spatial Distance 2	1	0.1958	0.1958	0.0000	0.0000	0.0000	0.5000	0.1556	0.1556	0.0000	0.0000	0.0000	0.5000
	1.5	0.8042	0.0046	0.0000	0.5000	−0.5000	1.0000	0.7491	0.0031	0.0000	0.5000	−0.5000	1.0000
	2	0.9817	0.0000	−0.5000	0.5000	−1.0000	1.0000	0.9699	0.0000	−0.5000	0.5000	−1.0000	1.0000
Temporal Distance 2	1	0.0041	0.0041	0.0000	0.0000	−0.5000	0.0000	0.0019	0.0019	0.0000	0.0000	−0.5000	0.0000
	1.5	0.0000	0.1025	−0.5000	0.0000	−1.0000	0.0000	0.0000	0.0546	−0.5000	0.0000	−1.0000	0.0000
	2	0.0000	0.3714	−1.0000	0.0000	−1.5000	0.0000	0.0000	0.2343	−1.0000	0.0000	−1.5000	0.0000
Social Distance 2	1	0.0082	0.0082	0.0000	0.0000	0.0000	0.0000	0.0085	0.0085	0.0000	0.0000	0.0000	0.0000
	1.5	0.0002	0.0912	0.0000	0.0000	−0.5000	0.0000	0.0002	0.0928	0.0000	0.0000	−0.5000	0.0000
	2	0.0000	0.2698	0.0000	0.0000	−0.5000	0.0000	0.0000	0.2731	0.0000	0.0000	−1.0000	0.0000
Hypothetical Distance 2	1	0.0112	0.0112	0.0000	0.0000	−0.5000	0.0000	0.0091	0.0091	0.0000	0.0000	−0.5000	0.0000
	1.5	0.0001	0.1978	−0.5000	0.0000	−1.0000	0.0000	0.0001	0.1624	−0.5000	0.0000	−1.0000	0.0000
	2	0.0000	0.5570	−1.0000	0.0000	−1.0000	0.0000	0.0000	0.4860	−1.0000	0.0000	−1.0000	0.0000
Hypothetical Distance 3	1	0.2192	0.2192	0.0000	0.0000	0.0000	0.0000	0.2216	0.2216	0.0000	0.0000	0.0000	0.0000
	1.5	0.7424	0.0128	0.0000	0.0000	0.0000	0.5000	0.7444	0.0131	0.0000	0.0000	−0.2500	0.5000
	2	0.9531	0.0005	0.0000	0.5000	−0.5000	0.7500	0.9535	0.0005	0.0000	0.5000	−0.5000	1.0000
Hypothetical Distance 4	1	0.0000	0.0000	0.5000	0.5000	0.0000	0.7500	0.0001	0.0001	0.5000	0.5000	0.0000	1.0000
	1.5	0.0057	0.0000	0.0000	0.7500	0.0000	1.0000	0.0126	0.0000	0.0000	1.0000	0.0000	1.0000
	2	0.0554	0.0000	0.0000	1.0000	0.0000	1.0000	0.0963	0.0000	0.0000	1.0000	0.0000	1.1000
N	119 matched pairs							113 matched pairs					

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
Number of Neighbors: 1.
Caliper for landslides: 0.010.
Caliper for drought: 0.020Source: Authors.

Data availability

Data will be made available on request.

References

Alcántara Rodríguez, M., Angueyra, A., Cleef, A.M., Van Andel, T., 2018. Ethnobotany of the Sierra Nevada del Cocuy-Güicán: climate change and conservation strategies in the Colombian Andes. J. Ethnobiol. Ethnomed. 14 (1), 34. https://doi.org/10.1186/s13002-018-0227-6.

Ali, A., Erenstein, O., 2017. Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. Clim. Risk Manag. 16, 183–194. https://doi.org/10.1016/j.crm.2016.12.001.

Aristizábal, E., Sánchez, O., 2020. Spatial and temporal patterns and the socioeconomic impacts of landslides in the tropical and mountainous Colombian Andes. Disasters 44 (3), 596–618. https://doi.org/10.1111/disa.12391.

Austin, P.C., 2009. Balance diagnostics for comparing the distribution of baseline covariates between treatment groups in propensity-score matched samples. Stat. Med. 28 (25), 3083–3107. https://doi.org/10.1002/sim.3697.

Austin, P.C., 2011a. An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivar. Behav. Res. 46 (3), 399–424. https://doi.org/10.1080/00273171.2011.568786.

Austin, P.C., 2011b. Optimal caliper widths for propensity-score matching when estimating differences in means and differences in proportions in observational studies. Pharm. Stat. 10 (2), 150–161. https://doi.org/10.1002/pst.433.

Azadi, Y., Yazdanpanah, M., Mahmoudi, H., 2019. Understanding smallholder farmers' adaptation behaviors through climate change beliefs, risk perception, trust, and psychological distance: evidence from wheat growers in Iran. J. Environ. Manage. 250. https://doi.org/10.1016/j.jenvman.2019.109456.

Bar-Anan, Y., Liberman, N., Trope, Y., 2006. The association between psychological distance and construal level: evidence from an implicit association test. J. Exp. Psychol. Gen. 135 (4), 609–622. https://doi.org/10.1037/0096-3445.135.4.609.

Barrucand, M.G., Giraldo Vieira, C., Canziani, P.O., 2017. Climate change and its impacts: perception and adaptation in rural areas of Manizales, Colombia. Clim. Dev. 9 (5), 415–427. https://doi.org/10.1080/17565529.2016.1167661.

Becker, S., Sparks, P., 2020. "It never rains in California": constructions of drought as a natural and social phenomenon. Weather Clim. Extremes 29, 100257. https://doi.org/10.1016/j.wace.2020.100257.

Bergquist, M., Nilsson, A., Schultz, P.W., 2019. Experiencing a severe weather event increases concern about climate change. Front. Psychol. 10. https://doi.org/10.3389/fpsyg.2019.00220.

Bonfrer, I., Breebaart, L., Van de Poel, E., 2016. The effects of Ghana's National Health Insurance Scheme on Maternal and Infant Health Care utilization. PLoS One 11 (11), e0165623. https://doi.org/10.1371/journal.pone.0165623.

Borick, C. P., Rabe, B. G. (2017). Personal Experience, Extreme Weather Events, and Perceptions of Climate Change. In: Oxford Research Encyclopedia of Climate Science. Oxford University Press. doi: 10.1093/acrefore/9780190228620.013.311.

Botero, H., Barnes, A., Perez, L., Rios, D., Ramirez-Villegas, J., 2021. Classifying climate change perceptions of bean breeders in Santander-Colombia. Clim. Dev. 13 (8), 663–676. https://doi.org/10.1080/17565529.2020.1848782.

Bravo-Ureta, B.E., Greene, W., Solís, D., 2012. Technical efficiency analysis correcting for biases from observed and unobserved variables: an application to a natural resource management project. Empir. Econ. 43 (1), 55–72. https://doi.org/10.1007/s00181-011-0491-y.

Caliendo, M., Kopeinig, S., 2008. Some practical guidance for the implementation of propensity score matching. J. Econ. Surv. 22 (1), 31–72. https://doi.org/10.1111/j.1467-6419.2007.00527.x.

Cameron, A. C., Trivedi, P. K. (2005). *Microeconometrics Methods and Applications* (1st ed.). Cambridge University Press.

Cano, A., Castro Campos, B., 2024. Drivers of farmers' adaptive behavior to climate change: the 3F-SEC framework. J. Rural. Stud. 109, 103343. https://doi.org/10.1016/j.jrurstud.2024.103343.

Carlton, J.S., Mase, A.S., Knutson, C.L., Lemos, M.C., Haigh, T., Todey, D.P., Prokopy, L.S., 2016. The effects of extreme drought on climate change beliefs, risk perceptions, and adaptation attitudes. Clim. Change 135 (2), 211–226. https://doi.org/10.1007/s10584-015-1561-5.

Chu, H., Yang, J.Z., 2019. Emotion and the psychological distance of climate change. Sci. Commun. 41 (6), 761–789. https://doi.org/10.1177/1075547019889637.

Craig, C.A., Feng, S., Gilbertz, S., 2019. Water crisis, drought, and climate change in the southeast United States. Land Use Policy 88, 104110. https://doi.org/10.1016/j.landusepol.2019.104110.

Dai, J., Kesternich, M., Löschel, A., Ziegler, A., 2015. Extreme weather experiences and climate change beliefs in China: an econometric analysis. Ecol. Econ. 116, 310–321. https://doi.org/10.1016/j.ecolecon.2015.05.001.

Dang, H.L., Li, E., Nuberg, I., Bruwer, J., 2014. Understanding farmers' adaptation intention to climate change: a structural equation modelling study in the Mekong Delta, Vietnam. SEnvironmental Science & Policy 41, 11–22. https://doi.org/10.1016/j.envsci.2014.04.002.

Dehejia, R.H., Wahba, S., 2002. Propensity score-matching methods for nonexperimental causal studies. Rev. Econ. Stat. 84 (1), 151–161. https://doi.org/10.1162/003465302317331982.

Delfiyan, F., Yazdanpanah, M., Forouzani, M., Yaghoubi, J., 2021. Farmers' adaptation to drought risk through farm–level decisions: the case of farmers in Dehloran county. Southwest of Iran. Climate and Development 13 (2), 152–163. https://doi.org/10.1080/17565529.2020.1737797.

Deng, Y., Wang, M., Yousefpour, R., 2017. How do people's perceptions and climatic disaster experiences influence their daily behaviors regarding adaptation to climate change? — a case study among young generations. Sci. Total Environ. 581–582, 840–847. https://doi.org/10.1016/j.scitotenv.2017.01.022.

Dhanya, P., Ramachandran, A., 2016. Farmers' perceptions of climate change and the proposed agriculture adaptation strategies in a semi arid region of south India. J. Integr. Environ. Sci. 13 (1), 1–18. https://doi.org/10.1080/1943815X.2015.1062031.

Diggs, D.M., 1991. Drought experience and perception of climatic change among great plain farmers. Great Plan Research 1 (1), 114–132.

Epanchin-Niell, R., Kuwayama, Y., Walls, M., 2017. Spatial-dynamic complexities of climate challenge for rural areas: Integrating resource and regional economic insights. Am. J. Agric. Econ. 99 (2), 447–463. https://doi.org/10.1093/ajae/aaw116.

Estifanos, T.K., Polyakov, M., Pandit, R., Hailu, A., Burton, M., 2020. The impact of protected areas on the rural households' incomes in Ethiopia. Land Use Policy 91, 104349. https://doi.org/10.1016/j.landusepol.2019.104349.

Fahad, S., Inayat, T., Wang, J., Dong, L., Hu, G., Khan, S., Khan, A., 2020. Farmers' awareness level and their perceptions of climate change: a case of Khyber Pakhtunkhwa province. Pakistan. Land Use Policy 96, 104669. https://doi.org/10.1016/j.landusepol.2020.104669.

Freire-González, J., Decker, C., Hall, J.W., 2017. The Economic Impacts of Droughts: a framework for analysis. Ecol. Econ. 132, 196–204. https://doi.org/10.1016/j.ecolecon.2016.11.005.

Funderburg, R.G., Nixon, H., Boarnet, M.G., Ferguson, G., 2010. New highways and land use change: results from a quasi-experimental research design. Transp. Res. A Policy Pract. 44 (2), 76–98. https://doi.org/10.1016/j.tra.2009.11.003.

Garcia-Delgado, H., Petley, D.N., Bermúdez, M.A., Sepúlveda, S.A., 2022. Fatal landslides in Colombia (from historical times to 2020) and their socio-economic impacts. Landslides 19 (7), 1689–1716. https://doi.org/10.1007/s10346-022-01870-2.

Garrido, M.M., Kelley, A.S., Paris, J., Roza, K., Meier, D.E., Morrison, R.S., Aldridge, M.D., 2014. Methods for constructing and assessing propensity scores. Health Serv. Res. 49 (5), 1701–1720. https://doi.org/10.1111/1475-6773.12182.

Gebrehiwot, T., van der Veen, A., 2015. Farmers prone to drought risk: why some farmers undertake farm-level risk-reduction measures while others not? Environ. Manag. 55 (3), 588–602. https://doi.org/10.1007/s00267-014-0415-7.

Gebrehiwot, T., van der Veen, A., 2021. Farmers' drought experience, risk perceptions, and behavioural intentions for adaptation: evidence from Ethiopia. Clim. Dev. 13 (6), 493–502. https://doi.org/10.1080/17565529.2020.1806776.

Goldfarb, A., Tucker, C., Wang, Y., 2022. Conducting research in marketing with quasi-experiments. J. Mark. 86 (3), 1–20. https://doi.org/10.1177/00222429221082977.

Guido, Z., Zimmer, A., Lopus, S., Hannah, C., Gower, D., Waldman, K., Krell, N., Sheffield, J., Caylor, K., Evans, T., 2020. Farmer forecasts: impacts of seasonal rainfall expectations on agricultural decision-making in Sub-Saharan Africa. Clim. Risk Manag. 30, 100247. https://doi.org/10.1016/j.crm.2020.100247.

Guillard, M., Navarro, O., Cortes, S., Fleury-Bahi, G., 2021. How do we adapt when we are faced with the effects of climate change? Int. J. Disaster Risk Reduct. 65, 102586. https://doi.org/10.1016/j.ijdrr.2021.102586.

Gupta, A.K., Negi, M., Nandy, S., Kumar, M., Singh, V., Valente, D., Petrosillo, I., Pandey, R., 2020. Mapping socio-environmental vulnerability to climate change in different altitude zones in the Indian Himalayas. Ecol. Ind. 109, 105787. https://doi.org/10.1016/j.ecolind.2019.105787.

Halperin, A., Walton, P., 2018. The Importance of place in communicating climate change to different facets of the American Public. Weather Clim. Soc. 10 (2), 291–305. https://doi.org/10.1175/WCAS-D-16-0119.1.

Ham, J.C., Li, X., Reagan, P.B., 2011. Matching and semi-parametric IV estimation, a distance-based measure of migration, and the wages of young men. J. Econ. 161 (2), 208–227. https://doi.org/10.1016/j.jeconom.2010.12.004.

Harder, V.S., Stuart, E.A., Anthony, J.C., 2010. Propensity score techniques and the assessment of measured covariate balance to test causal associations in psychological research. Psychol. Methods 15 (3), 234–249. https://doi.org/10.1037/a0019623.

Heckman, J.J., Lalonde, R.J., Smith, J.A., 1999. The economics and econometrics of active labor market programs. Handbook of Labor Economics 3 (1), 1865–2097. https://doi.org/10.1016/S1573-4463(99)03012-6.

IPCC. (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Jacovidis, J.N., Foelber, K.J., Horst, S.J., 2017. The effect of propensity score matching method on the quantity and quality of matches. J. Exp. Educ. 85 (4), 535–558. https://doi.org/10.1080/00220973.2016.1250209.

Keller, E., Marsh, J.E., Richardson, B.H., Ball, L.J., 2022. A systematic review of the psychological distance of climate change: towards the development of an evidence-based construct. J. Environ. Psychol. 81, 101822. https://doi.org/10.1016/j.jenvp.2022.101822.

Keshavarz, M., Karami, E., 2016. Farmers' pro-environmental behavior under drought: application of protection motivation theory. J. Arid Environ. 127, 128–136. https://doi.org/10.1016/j.jaridenv.2015.11.010.

Kim, K., Ahn, (Grace), S.J., 2019. The moderating role of cultural background in temporal framing: focusing on climate change awareness advertising. Asian J. Commun. 29 (4), 363–385. https://doi.org/10.1080/01292986.2019.1624793.

Kolar, A., Steiner, P.M., 2021. The role of sample size to attain statistically comparable groups – a required data preprocessing step to estimate causal effects with observational data. Eval. Rev. 45 (5), 195–227. https://doi.org/10.1177/0193841X211053937.

Konisky, D.M., Hughes, L., Kaylor, C.H., 2016. Extreme weather events and climate change concern. Clim. Change 134 (4), 533–547. https://doi.org/10.1007/s10584-015-1555-3.

Li, J., Qin, P., Quan, Y., Tan-Soo, J.-S., 2023. Using Protection Motivation Theory to examine information-seeking behaviors on climate change. Glob. Environ. Chang. 81, 102698. https://doi.org/10.1016/j.gloenvcha.2023.102698.

Li, X., Cao, Z., Shi, X., 2022. How do farmer's disaster experiences influence their climate change perception and adaptation? Clim. Dev. 14 (6), 523–536. https://doi.org/10.1080/17565529.2021.1949572.

Liberman, N., Trope, Y., 1998. The role of feasibility and desirability considerations in near and distant future decisions: a test of temporal construal theory. J. Pers. Soc. Psychol. 75 (1), 5–18. https://doi.org/10.1037/0022-3514.75.1.5.

Liberman, N., Trope, Y., 2014. Traversing psychological distance. Trends Cogn. Sci. 18 (7), 364–369. https://doi.org/10.1016/j.tics.2014.03.001.

Liberman, N., Trope, Y., Stephan, E., 2007. Psychological Distance. In: Kruglanski, A.W., Higgins, E.T. (Eds.), Social Psychology Handbook of Basic Principles. The Guilford Press, pp. 353–381.

Lin, S., Shaw, D., Ho, M.-C., 2008. Why are flood and landslide victims less willing to take mitigation measures than the public? Nat. Hazards 44 (2), 305–314. https://doi.org/10.1007/s11069-007-9136-z.

Loy, L.S., Spence, A., 2020. Reducing, and bridging, the psychological distance of climate change. J. Environ. Psychol. 67, 101388. https://doi.org/10.1016/j.jenvp.2020.101388.

Lyons, B.A., Hasell, A., Stroud, N.J., 2018. Enduring extremes? Polar vortex, drought, and climate change beliefs. Environ. Commun. 12 (7), 876–894. https://doi.org/10.1080/17524032.2018.1520735.

Maddux, J.E., Rogers, R.W., 1983. Protection motivation and self-efficacy: a revised theory of fear appeals and attitude change. J. Exp. Soc. Psychol. 19 (5), 469–479.

Mahony, C.R., Cannon, A.J., 2018. Wetter summers can intensify departures from natural variability in a warming climate. Nat. Commun. 9 (1), 783. https://doi.org/10.1038/s41467-018-03132-z.

Marin, A., 2010. Riders under storms: contributions of nomadic herders' observations to analysing climate change in Mongolia. Glob. Environ. Chang. 20 (1), 162–176. https://doi.org/10.1016/j.gloenvcha.2009.10.004.

Mertens, K., Jacobs, L., Maes, J., Poesen, J., Kervyn, M., Vranken, L., 2018. Disaster risk reduction among households exposed to landslide hazard: a crucial role for self-efficacy? Land Use Policy 75, 77–91. https://doi.org/10.1016/j.landusepol.2018.01.028.

Miller, N., Tack, J., Bergtold, J., 2021. The impacts of warming temperatures on US Sorghum yields and the potential for adaptation. Am. J. Agric. Econ. 103 (5), 1742–1758. https://doi.org/10.1111/ajae.12223.

Mosavian, S.H., Rostami, F., Tatar, M., 2023. Modeling farmers' intention to water protection behavior: a new extended version of the protection motivation theory. J. Environ. Psychol. 90, 102036. https://doi.org/10.1016/j.jenvp.2023.102036.

Muench, S., Bavorova, M., Pradhan, P., 2021. Climate change adaptation by smallholder tea farmers: a case study of Nepal. Environ Sci Policy 116, 136–146. https://doi.org/10.1016/j.envsci.2020.10.012.

Murtinho, F., Tague, C., de Bievre, B., Eakin, H., Lopez-Carr, D., 2013. Water scarcity in the andes: a comparison of local perceptions and observed climate, land use and socioeconomic changes. Hum. Ecol. 41 (5), 667–681. https://doi.org/10.1007/s10745-013-9590-z.

Neisi, M., Bijani, M., Abbasi, E., Mahmoudi, H., Azadi, H., 2020. Analyzing farmers' drought risk management behavior: evidence from Iran. J. Hydrol. 590, 125243. https://doi.org/10.1016/j.jhydrol.2020.125243.

Pakmehr, S., Yazdanpanah, M., Baradaran, M., 2020. How collective efficacy makes a difference in responses to water shortage due to climate change in southwest Iran. Land Use Policy 99, 104798. https://doi.org/10.1016/j.landusepol.2020.104798.

Panda, A., 2016. Exploring climate change perceptions, rainfall trends and perceived barriers to adaptation in a drought affected region in India. Nat. Hazards 84 (2), 777–796. https://doi.org/10.1007/s11069-016-2456-0.

Pardo Martínez, C.I., Alfonso Piña, W.H., Moreno, S.F., 2018. Prevention, mitigation and adaptation to climate change from perspectives of urban population in an emerging economy. J. Clean. Prod. 178, 314–324. https://doi.org/10.1016/j.jclepro.2017.12.246.

Parsons, L., Nielsen, J.Ø., 2021. The subjective climate Migrant: climate perceptions, their Determinants, and relationship to migration in Cambodia. Ann. Am. Assoc. Geogr. 111 (4), 971–988. https://doi.org/10.1080/24694452.2020.1807899.

Peng, Y., Xu, Z., Wei, P., Cheng, L., 2022. Smallholder farmers' behavioral preferences under the impact of climate change: a comparative analysis of two agricultural areas in China. Front. Earth Sci. 10, 1010733. https://doi.org/10.3389/feart.2022.1010733.

Pinto, J.O., Monaghan, A.J., Delle Monache, L., Vanvyve, E., Rife, D.L., 2014. Regional assessment of sampling techniques for more efficient dynamical climate downscaling. J. Clim. 27 (4), 1524–1538. https://doi.org/10.1175/JCLI-D-13-00291.1.

Pirracchio, R., Resche-Rigon, M., Chevret, S., 2012. Evaluation of the Propensity score methods for estimating marginal odds ratios in case of small sample size. BMC Med. Res. Method. 12 (1), 70. https://doi.org/10.1186/1471-2288-12-70.

Quaye, F., Nadolnyak, D., Hartarska, V., 2018. Climate change impacts on farmland values in the Southeast United States. Sustainability 10 (10), 3426. https://doi.org/10.3390/su10103426.

Ricart, S., Gandolfi, C., Castelletti, A., 2023. Climate change awareness, perceived impacts, and adaptation from farmers' experience and behavior: a triple-loop review. Reg. Environ. Chang. 23 (3), 82. https://doi.org/10.1007/s10113-023-02078-3.

Rodríguez Pacheco, F.L., Mejía Rodríguez, D.L., Sánchez Buitrago, J.O., 2022. Conocimientos y percepciones sobre el cambio climático en estudiantes universitarios. Diversitas 18 (1). https://doi.org/10.15332/22563067.6305.

Rodríguez-Barillas, M., Poortvliet, P.M., Klerkx, L., 2024. Unraveling farmers' interrelated adaptation and mitigation adoption decisions under perceived climate change risks. J. Rural. Stud. 109, 103329. https://doi.org/10.1016/j.jrurstud.2024.103329.

Rodríguez-Cruz, L.A., Niles, M.T., 2021. Awareness of climate change's impacts and motivation to adapt are not enough to drive action: a look of Puerto Rican farmers after Hurricane Maria. PLoS One 16 (1), e0244512. https://doi.org/10.1371/journal.pone.0244512.

Rogers, R.W., 1975. A protection motivation theory of fear appeals and attitude change. J. Psychol. 91, 93–114. https://doi.org/10.1080/00223980.1975.9915803.

Rogers, R. W. (1983). *Cognitive and Physiological Processes in Fear Appeals and Attitude Change: A Revised Theory of Protection Motivation* (J. T. Cacioppo, R. E. Petty, Eds.; pp. 153–177). https://www.researchgate.net/publication/229068371.

Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70 (1), 41–55. https://doi.org/10.2307/2335942.

Saleh Safi, A., James Smith, W., Liu, Z., 2012. Rural Nevada and climate change: vulnerability, beliefs, and risk perception. Risk Anal. 32 (6), 1041–1059. https://doi.org/10.1111/j.1539-6924.2012.01836.x.

Scarpa, R., Thiene, M., 2011. Organic food choices and Protection Motivation Theory: addressing the psychological sources of heterogeneity. Food Qual. Prefer. 22 (6), 532–541. https://doi.org/10.1016/j.foodqual.2011.03.001.

Simelton, E., Quinn, C.H., Batisani, N., Dougill, A.J., Dyer, J.C., Fraser, E.D.G., Mkwambisi, D., Sallu, S., Stringer, L.C., 2013. Is rainfall really changing? Farmers' perceptions, meteorological data, and policy implications. Clim. Dev. 5 (2), 123–138. https://doi.org/10.1080/17565529.2012.751893.

Skevas, T., Massey, R., Grashuis, J., 2022. Farmer adoption and intensity of use of extreme weather adaptation and mitigation strategies: evidence from a sample of Missouri farmers. Clim. Change 174 (1–2), 18. https://doi.org/10.1007/s10584-022-03439-3.

Slegers, M.F.W., 2008. "If only it would rain": farmers' perceptions of rainfall and drought in semi-arid central Tanzania. J. Arid Environ. 72 (11), 2106–2123. https://doi.org/10.1016/j.jaridenv.2008.06.011.

Spegel, E., Ek, K., 2022. Valuing the impacts of landslides: a choice experiment approach. Econ. Disasters Clim. Change 6 (1), 163–181. https://doi.org/10.1007/s41885-021-00101-7.

Stuart, E.A., 2010. Matching methods for causal inference: a review and a look forward. Stat. Sci. 25 (1). https://doi.org/10.1214/09-STS313.

Sutcliffe, C., Holman, I., Goodwin, D., Salmoral, G., Pardthaisong, L., Visessri, S., Ekkawatpanit, C., Rey, D., 2024. Which factors determine adaptation to drought amongst farmers in Northern Thailand? Investigating farmers' appraisals of risk and adaptation and their exposure to drought information communications as determinants of their adaptive responses. Mitig. Adapt. Strat. Glob. Chang. 29 (1), 6. https://doi.org/10.1007/s11027-023-10099-w.

Trope, Y., Liberman, N., 2003. Temporal construal. Psychol. Rev. 110 (3), 403–421. https://doi.org/10.1037/0033-295X.110.3.403.

Trope, Y., Liberman, N., Wakslak, C., 2007. Construal levels and psychological distance: effects on representation, prediction, evaluation, and behavior. J. Consum. Psychol. 17 (2), 83–95. https://doi.org/10.1016/S1057-7408(07)70013-X.

Truelove, H.B., Carrico, A.R., Thabrew, L., 2015. A socio-psychological model for analyzing climate change adaptation: a case study of Sri Lankan paddy farmers. Glob. Environ. Chang. 31, 85–97. https://doi.org/10.1016/j.gloenvcha.2014.12.010.

van Duinen, R., Filatova, T., Geurts, P., van der Veen, A., 2015. Coping with drought risk: empirical analysis of farmers' drought adaptation in the south-west Netherlands. Reg. Environ. Chang. 15 (6), 1081–1093. https://doi.org/10.1007/s10113-014-0692-y.

Venkatappa, M., Sasaki, N., Han, P., Abe, I., 2021. Impacts of droughts and floods on croplands and crop production in Southeast Asia – an application of Google Earth Engine. Sci. Total Environ. 795, 148829. https://doi.org/10.1016/j.scitotenv.2021.148829.

Vranken, L., Van Turnhout, P., Van Den Eeckhaut, M., Vandekerckhove, L., Poesen, J., 2013. Economic valuation of landslide damage in hilly regions: a case study from Flanders, Belgium. Sci. Total Environ. 447, 323–336. https://doi.org/10.1016/j.scitotenv.2013.01.025.

West, C.T., Roncoli, C., Ouattara, F., 2008. Local perceptions and regional climate trends on the Central Plateau of Burkina Faso. Land Degrad. Dev. 19 (3), 289–304. https://doi.org/10.1002/ldr.842.

Winter, M.G., Peeling, D., Palmer, D., Peeling, J., 2019. Economic impacts of landslides and floods on a road network. AUC GEOGRAPHICA 54 (2), 207–220. https://doi.org/10.14712/23361980.2019.18.

Yazdanpanah, M., Zobeidi, T., Warner, L.A., Löhr, K., Lamm, A., Sieber, S., 2023. Shaping farmers' beliefs, risk perception and adaptation response through Construct Level Theory in the southwest Iran. Sci. Rep. 13 (1), 5811. https://doi.org/10.1038/s41598-023-32564-x.