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Climate and soil conditions shape farmers' climate change adaptation preferences

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Abstract
Climate change poses a significant threat to agriculture and challenges farmers' adaptive capacity. Understanding how farmers evaluate and prioritize different climate change adaptation measures under consideration of their natural environment is crucial yet widely overlooked. This study determines the relative importance that farmers attach to different adaptation measures and explores the role of climatic and soil conditions in this context. It uses a best-worst scaling experiment with German arable farmers in combination with geospatial climate and soil information. Findings reveal a preference for incremental adaptation measures over more transformative ones. However, preferences varied considerably with average local temperature, precipitation, and soil quality. The finding that farmers' adaptation preferences are highly diverse and context-specific calls for tailored policies. It is crucial for policymakers to have a thorough understanding of farmers' adaptation preferences. Based on the results, the study discusses multiple actions that policymakers can take to incentivize farmers to favor more effective adaptation measures.

KEYWORDS
agriculture, best-worst scaling, climate, climate change adaptation, land use, soil

JEL CLASSIFICATION
Q54, Q12, Q15, D9

1 | INTRODUCTION

Climate change poses unprecedented challenges to various sectors globally. According to the latest projections from the Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report (AR6) global temperatures are anticipated to rise by approximately 2.7°C above pre-industrial levels by the end of the century, with a 2°C increase already expected by 2050, if the current trajectory of greenhouse gas emissions persists (IPCC, 2022). Agriculture is one of the sectors that is particularly vulnerable to the negative effects of climate change. Rising temperatures, changes in precipitation patterns, and an increase in extreme weather events can affect crop yields, increase the risk of crop failure (Schmitt et al., 2022), and amplify pressure from pests and diseases (Deutsch et al., 2018). Projections indicate that these impacts are likely to intensify in the coming decades (e.g., Calzadilla et al., 2013; Fischer et al., 2005; Lobell et al., 2008), compelling farmers to adapt to increasingly variable conditions. Although adaptation to climate variability has historically been a fundamental aspect of agricultural practice (Pei et al., 2015), the accelerated rate and heightened severity of current and anticipated climate change introduce novel challenges that necessitate more rapid and strategic adaptive measures (Dell et al., 2014).

However, there is no one-size-fits-all solution to climate change adaptation (Hansen & Bi, 2017). Farmers and farms, even in contiguous regions, encounter significant variability in production environments, due to heterogeneity in micro- and macro-climates and soil conditions (Njuki et al., 2018; Tsionas, 2002). Consequently, the impact of climatic changes is not uniform and they must adopt distinct adaptation measures tailored to their specific contextual conditions (Mérel & Gammans, 2021; Ortiz-Bobea et al., 2021; Schlenker & Roberts, 2009; Schmitt et al., 2022). The natural environment has both direct and indirect pathways through which it affects farmers' production choices. For example, weather affects plant physiological response, directly impacting yield, and weather conditions can also affect the presence of pests and disease, indirectly impacting yield. With heterogeneity in the natural environment causing heterogeneous impacts on production, these local biophysical conditions should be considered in farmer decision-making and preference formation.

This study analyzes German farmers' preference for climate change adaptation activities related to crop cultivation, and how preferences are linked to local environmental conditions. A best-worst scaling (BWS) experiment was used to determine the relative importance that farmers attach to different adaptation measures within the context of German arable farming. The presented research approach takes into account how diverse local biophysical conditions, in this case, local climate and soil quality, can influence preferences regarding climate change adaptation.

Studies on climate change adaptation have often focused on either identifying the factors that drive farmers to adopt specific adaptation measures (e.g., Bryan et al., 2013) or adaptation impacts (e.g., Asfaw et al., 2012), or both (e.g., Di Falco et al., 2014). Also, the relationship between farms' biophysical environment and farmers' management choices (such as climate change adaptation) has gained increasing attention in recent years. Local environmental conditions have been found to affect farmers' land-use decisions (Ramsey et al., 2021; Stetter & Sauer, 2024; Stetter et al., 2024), insurance uptake (Möhring et al., 2020), risk preferences (Villacis et al., 2021), or input use (Möhring et al., 2021; Wimmer et al., 2024). For example, recent findings by Wimmer et al. (2024) show that warmer conditions shift production from cereals and oilseeds to root crops for German farmers, while droughts reduce the supply of key crops, especially corn, and decrease fertilizer use. Despite the abundance of research in this area, a recurring criticism is the insufficient consideration of farmers' needs, preferences, and their natural environments in the context of climate change adaptation (Crane et al., 2011; Dolinska et al., 2023; Hellin et al., 2022). This is a critical issue as farmers are ultimately responsible for implementing adaptation measures on their farms and determining the overall success of climate change adaptation efforts (Hellin et al., 2022).

This study makes three contributions to the literature on climate change adaptation in agriculture. First, while effective climate change adaptation measures are generally well-understood, this research adds value by examining not only their effectiveness but also their relevance to farmers themselves. By focusing on the decision-making process of farmers in choosing among these measures, we aim to provide insights into the practical implementation of adaptation measures, which is a crucial aspect often overlooked in the literature. Second, the analysis provides a careful evaluation of how farmers' preferences are linked to environmental conditions, taking into account the fact that decision-makers face multiple related options that are not independent of each other. We demonstrate how changes in climatic and soil conditions can lead to complex interrelated adjustments regarding individual farmers' preferences for climate change adaptation measures. The third key contribution of this study is the methodology employed to identify farmers' preferences for climate change adaptation measures. Unlike conventional methods that assess preferences for individual measures in isolation, this study adopts a broader perspective by evaluating adaptation measures collectively and in mutual comparison. While previous research often relied on Likert-scale-type ranking methods or approve/disapprove questions (Caputo & Lusk, 2020), we chose to employ the best-worst scaling method (BWS) to elicit farmers' preferences. BWS offers several cognitive and methodological advantages over traditional ranking methods (Louviere et al., 2015). By asking farmers to choose the best and worst options within sets of adaptation measures, BWS goes beyond simply identifying favored measures and allows for a nuanced understanding of farmers' perspectives on climate change adaptation, and provides insights into the relative value of adaptation measures for specific farming conditions.

The study finds that German crop farmers prefer low-cost, gradual climate change adaptation methods such as crop rotation diversification and conservation tillage. Preferences varied significantly across farms and were influenced by local biophysical conditions. Drier areas were linked to crop rotation adjustments and reduced tillage, while wetter areas were associated with the use of cover crops and mixed cropping. Similarly, hotter con-

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

ditions favored the use of resilient crops, while cooler conditions were linked to diversified rotations. Soil quality also played a role, with cover crops and resilient crops preferred on poorer soils. Farmers showed limited interest in insurance, irrigation, and precision farming approaches for climate change adaptation.

The remainder of this article is structured as follows. Section 2 gives a brief overview of potential climate change adaptation measures in crop farming. In Section 3, the study design, the data collection procedure, and empirical strategy are presented. Section 4 summarizes the findings of the study, and is followed by an in-depth discussion of the results and their limitations (Section 5). The article closes with a few concluding remarks in Section 6.

2 | CLIMATE CHANGE ADAPTATION MEASURES IN ARABLE CROP FARMING

Adaptation measures intent on mitigating potential damage as well as taking advantage of opportunities that arise (IPCC, 2007). In the agricultural sector, these measures are diverse and influenced by climatic factors; farm types; locations; and economic, political, and institutional conditions (Bryant et al., 2000; Smit & Skinner, 2002). Olesen et al. (2011) found that farmers across Europe perceived changing crop varieties, sowing dates, fertilizer, and pesticide use as the most important adaptation measures. Iglesias and Garrote (2015) provide an assessment of the most important adaptation measures for agricultural water management in Europe. They found that, at the farm level, the improvement of drainage systems and the creation of small water reservoirs are among the most sensible measures.

In German agriculture, adaptation measures include the diversification of cultivation, breeding of tolerant and resistant varieties, conservation tillage, situation-related plant protection, and monitoring and prediction of rodent populations (Schimmelpfennig et al., 2018). Kaye and Quemada (2017) emphasize the role of cover crops that are tailored to regional and local climate conditions. Regarding other crop management practices, Himanen et al. (2016) identified mixed cropping as a viable climate change adaptation measure, noting its benefits in improving yield security, enhancing nutrient and protein self-sufficiency, maintaining soil health, reducing pest pressure, and regulating water dynamics. Mase et al. (2017) show that new technologies, local protection practices, and insurance are three main measures that farmers primarily rely on in the U.S. context. Key adaptation measures discussed in the literature are listed in Table 1.

3 | METHODS

3.1 | Best-worst scaling and random utility theory

To capture farmers' climate adaptation preferences across a broad spectrum of measures, this study uses the best-worst scaling (BWS) object case. In this approach, respondents are asked to choose two items from a choice set containing three or more items, with their choices reflecting the extremes (best and worst, or most important and least important) of a particular standard (Aizaki et al., 2014). BWS has the advantage that the task is easy for respondents (here farmers) to understand and therefore easy to answer. It also takes advantage of a person's tendency to recognize and consistently respond to extreme options, so that a single pair of best and worst choices can reveal a lot of information about a person's ranking of preferences (Marley & Louviere, 2005).

Previous studies found that BWS is more effective for assessing preferences compared to other rating methods. For instance, a study by Chrzan and Golovashkina (2006) compared BWS to six other methods including importance rating, constant sum, Q-sort, unbounded ratings, and magnitude estimation and found that BWS had greater discriminatory power and predictive validity than its alternatives. Another study by Menictas et al. (2012) compared confirmatory factor analysis and BWS and found that BWS better-captured people's behavior when choosing from a set of items.

In this study, we used BWS object case because it reduces the cognitive burden of ranking numerous intangible concepts simultaneously and helps respondents focus on the relative preference of each measure within the context of their specific farming operations (Marley & Louviere, 2005). We utilized a balanced incomplete block design (BIBD) (Green, 1974) to construct choice sets, incorporating 13 adaptation measures, each appearing four times within the design and each pair of measures appearing once, adhering to the optimal range of four to six items per decision set (Cohen, 2009). This process is repeated until all subsets have been evaluated (Fogarty & Aizaki, 2018). By breaking the list of adaptation measures down into sets and thus simplifying the decision-making process for respondents, a comprehensive evaluation of all presented adaptation measures is ensured (compare Marley & Louviere, 2005).

Conceptually, BWS uses the utility maximization concept and is based on random utility theory (RUT), which treats best and worst choices as utility-maximizing and minimizing decisions (McFadden, 1973). It assumes that a farmer n faces a choice among J alternative adaptation

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE

TABLE 1 Overview of selected climate change adaptation measures in crop farming from the literature.

	Altieri and Nicholls (2017)	Atlin et al. (2017)	Clements et al. (2011)	Di Falco et al. (2014)	Friedel et al. (2019)	Eggers et al. (2015)	Himanen et al. (2016)	Iglesias and Garrote (2015)	Kaye and Quemada (2017)	Klein et al. (2014)	Mase et al. (2017)	Meza et al. (2008)	Olesen et al. (2011)	Roco et al. (2017)	Schimmelpfennig et al. (2018)	Troost and Berger (2014)	Woods et al. (2017)
Biodiversification	X																
Conservation tillage	x		x		x	x		x		x	x				x		
Crop diversification			x	x				x			x		x	x			
Crop rotation					x					x			x				x
Cover crops									x	x				x			
Wood structures/hedges					x												
Mixed cropping							x										x
Double cropping												x					
Use of legumes									x								
Use of resistant varieties						x		x					x	x	x		x
Water harvesting	x		x														
Irrigation			x			x		x		x			x	x			x
Water reservoirs								x					x	x			
Changes in timing of practices													x	x		x	x
Monitoring								x							x		
Breeding		x	x										x		x		
Fertilization efficiency						x		x		x			x				
Plant protection						x							x		x		x
Technology			x					x			x						
Insurance			x	x				x			x						x
Off-farm income											x						

measures and obtains a certain level of utility from each alternative. Utility U_{nj} results from alternative j with $j = 1, \ldots, J$. It is assumed that the respondent chooses the adaptation measure that provides the greatest utility by choosing an alternative i only if:

$$U_{ni} > U_{nj}. \tag{1}$$

In this study, the utility U that farmer n derives from the selected pair of the perceived best (j) and worst (k) adaptation measures in each BWS question is the difference in utility between j and k plus an error term:

$$U_{nj} = \beta_j - \beta_k + \in_{nj} \tag{2}$$

where vector β is a utility coefficient of the best and worst measures relative to the measure that is normalized to zero for identification purposes (Caputo & Lusk, 2020). $\in_{nj}$ is a random, unobservable component. It is assumed that this process determines the most and least preferred measures based on the utility differences between them, as quantified by utility coefficients, guiding farmers to choose measures that maximize their benefits and minimize their drawbacks.

Several studies within the agricultural context have employed a conceptually similar framework (Caputo & Lusk, 2020; Dumbrell et al., 2016; Ola & Menapace, 2020). These studies, among others, demonstrate the applicability of random utility theory and BWS Case 1 to capture farmers' relative preferences for intangible objects like climate change adaptation measures. Examples of factors explored in these studies encompass food policies (Caputo & Lusk, 2020), market access constraints (Ola & Menapace, 2020), climate change mitigation practices (Jones et al., 2013), and carbon sequestration measures (Dumbrell et al., 2016).

3.2 | Study design and data

Based on a comprehensive literature review, important adaptation measures for arable farming in Germany were identified. After a list of different possible adaptation measures was drawn up, expert interviews were carried out with the aim of identifying the 13 most relevant adaptation measures for German arable farming (as determined by the balanced incomplete block design). The interviews also served as a preliminary test of the clarity and understanding of the measures' definitions. Table 2 includes the 13 adaptation measures identified for this study along with a brief description of each measure as provided to respondents during the survey.

Following the incorporation of feedback from the pretest phase, the finalized survey was launched online between January and March 2021. German apprenticing farmers listed on the agricultural education server ("Bildungsserver Agrar") were contacted via email and invited to participate in the survey. Only farms that cultivated arable crops were eligible to participate. In addition to the BWS experiment, the survey also collected information on several contextual factors such as farm characteristics (e.g., farm size, production focus, location, etc.), farmers' socioeconomic characteristics (e.g., age, education, etc.), and behavioral characteristics (e.g., risk attitude, perception of climate change, etc.). The BWS experiment consisted of 13 choice sets, presented to each respondent. An example of a choice set is shown in Figure S1.[1]

To describe farmers' natural environment (i.e., environmental conditions), climatic conditions and local soil quality were used. Climate, according to the World Meteorological Organization, is defined as the long-term average of weather conditions in a specific region, typically characterized over a 30-year period (Arguez & Vose, 2011). Relying on this definition, farmers' preferences were related to their local climatic conditions by using average temperature and average rainfall totals during the typical growing season from March to October averaged over the years 1991–2020, along with local soil quality. The meteorological data came from the German meteorological service (Deutscher Wetterdienst, DWD). The climate indicators relied on openly accessible daily gridded weather data at a 1 km^2 regular grid resolution (Razafimaharo et al., 2020). These data are generated through the interpolation of weather measurements obtained from a network comprising more than 1300 weather stations (Razafimaharo et al., 2020). For further insights into this dataset, additional information can be found in Rauthe et al. (2013) and Razafimaharo et al. (2020). The soil quality index used was acquired from the European Soil Data Centre (ESDAC) and reflects the soil biomass productivity of croplands in Europe (Panagos et al., 2022; Tóth et al., 2013). The indicator ranges from 0 (poor soil quality) to 10 (excellent soil quality). Figure 1 provides an overview of climatic and soil conditions in Germany. Finally, the meteorological and soil indices were spatially aggregated using area-weighted averages based on the postcode areas of the farm locations provided by the survey respondents. These aggregated indices were subsequently linked to the questionnaire responses.

[1] The BWS part of the survey was designed following a conventional approach by assuming a sequential choice process, meaning the best choice was presented on the left and the worst choice on the right. Based on the left to right reading direction that is common in Germany, it is reasonable to assume that respondents first make their best choice (Dumbrell et al., 2016).

TABLE 2 Adaptation measures and description.

Measures	Description
Precision farming	For example use of autonomous drones to spray weeds, use of robots (e.g., Farmdroid) for sowing and weed control, use of wireless sensors to collect data on soil compaction, soil fertility, the local climate, etc., or the site-specific application of fertilizers and pesticides.
Adjusted crop management rhythm	Change in the timing of the individual cultivation processes in the crops depending on the changing weather conditions. For example early ordering of maize or general change in the time of sowing and harvesting.
Adjusted plant protection management	Increased use of pesticides or change in the range of pesticides to combat the increased pest pressure. Diversification of crops and landscape management, use of beneficial insects, mechanical weed and pest control, use of biological pesticides.
Crop rotation diversification	Expansion and diversification of the range of crops for operational risk distribution, for example change of summer and winter culture as well as stalk and leaf crops, cultivation of legumes, under sown crops, etc.
Conservation tillage	Shallow tillage, near-ground return of plant residues/harvest residues in order to increase the organic matter of the soil. Avoidance of ground pressure, tire pressure regulation systems, ground-friendly tires of the machines, reduction of the wheel load, avoidance of driving on too damp ground, etc.
Adjusted fertilizer management	Adjustment of the fertilizer intensity, selection of fertilizers according to nitrogen form, determination of the needs-based N fertilization, determination of the nutrient content of organic fertilizers, optimized fertilization with organic fertilizers, field-specific fertilization, temporal and quantitative division into fertilizers, etc.
Cultivation of resilient crops	Introduction of climate-adapted and / or water-saving crops such as millet and rye, or energy crops such as cup plant or tall wheatgrass.
Cultivation of resilient crop varieties	Increased focus on drought-tolerant, frost-tolerant or pest-resistant varieties.
Cultivation of cover crops	Cultivation of catch crops in the seasonal gaps between two main crops.
Mixed cropping	Simultaneous cultivation of several types of crops on one area. Mixed species such as legumes and grain or cultivation of different varieties on one area. This also includes agroforestry systems in which the cultivation of perennial and annual crops is combined.
Irrigation	Use of sprinklers or drip irrigation, smart irrigation, such as irrigation methods based on soil moisture.
Insurance	Protection against extreme weather events (e.g., hail, drought, floods) and loss of earnings by means of damage or index insurance.
Business & income diversification	Establishment or expansion of branches of operations outside of arable farming, for example income combination through animal husbandry, tourism, pension and equestrian horse husbandry, community maintenance, etc.

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE

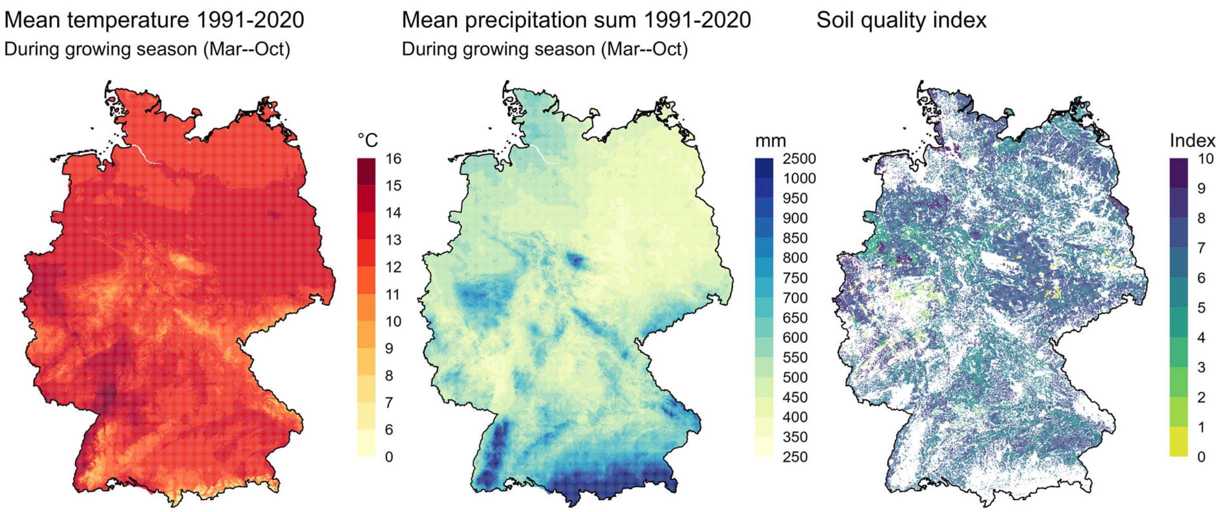

FIGURE 1 Overview of temperature and precipitation normals (1991–2020), and soil quality across Germany.

3.3 | Econometric analysis

Following the random utility theory, it is assumed that farmers will try to choose the adaptation measure that yields them the highest utility. Hence, the empirical structure of the utility function represents the process in which the alternatives and the natural environment of the farms are combined to influence the choice probabilities and thus the predictive capability of the choice model (Louviere et al., 2010). For the empirical specification of the model (see Equation 2), a mixed logit model (MXL) was used to account for preference heterogeneity in the utility function of the farmers. The unconditional probability that a farmer n selects j as best and k as worst is defined as:

$$P_{nj} = \int_{\beta} \prod_{t=1}^{T} \frac{e^{(\beta_{njt}-\beta_{nkt})}}{\sum_{l=1}^{J} \sum_{m=1}^{J} e^{(\beta_{nlt}-\beta_{nmt})-J}} f\left(\beta_n\right) d\beta_n \tag{3}$$

where t refers to one BWS question. $f(\beta_n)$ is the density of the preference parameters β_n, where the subscript n attached to β implies that β is different for each respondent (Caputo & Lusk, 2020; Nakano & Tsuge, 2019). The parameters were estimated using maximum likelihood estimation and 2000 Halton draws. Regarding the parameter distributions, the following assumptions were made:

$$\beta_n = \beta + \delta' z + \Gamma \upsilon_n \tag{4}$$

where β are constants in the distributions of the random preference parameters. z is a vector of observed variables that measures the heterogeneity in the means of the random parameters reflecting climate and soil conditions.

δ is a coefficient vector that enters the heterogeneous means of the distributions of the random parameters. This vector allows the integration of observed variations in the means of the random parameters, specifically addressing how precipitation, temperature, and soil quality *ceteris paribus* impact the values of these parameters.

υ_n captures individual-specific unexplained variation around the mean. Γ is a lower triangular matrix that allows correlation across the attribute-related random coefficients (Greene, 2017). This specification follows the approach by Hess and Rose (2012), who demonstrated that by allowing for correlation across random parameters, is it possible to capture scale heterogeneity alongside heterogeneity in utility coefficients. This is important in this context because farmers often realize that a single adaptation measure alone might not be sufficient to tackle climate risks and they therefore bundle multiple measures (Akter et al., 2023; Ishtiaque, 2023). For instance, Roesch-McNally et al. (2020) found that farmers in Oregon use irrigation in combination with enhanced nutrient management and shifted planting dates. Such phenomena have important consequences for the estimation procedure because they inevitably lead to a correlated coefficient structure. Ignoring this correlation could severely bias parameter estimates.

All random parameters were assumed to be normally distributed.[2] To address potential multicollinearity issues in the model, a standard normalization technique was employed, that is,In the BWS the coefficient of a chosen adaptation measure was fixed to zero. This chosen measure acts as a reference point for all other items. As a

[2] Although the normal distribution is a common assumption in mixed logit models, it is acknowledged that this may not perfectly capture the true underlying distribution (Hensher and Greene, 2003). However, the normal distribution offers advantages in terms of flexibility, ease of interpretation, and its ability to accommodate correlation between random parameters (Hess and Train, 2017; Train, 2001).

TABLE 3 Sample description and comparison with the population mean.

	Sample			Germany
	Mean	Median	SD	Population mean
Full-time farming (1 if yes, 0 otherwise)	.98	1	.15	.45[§]
Utilized agricultural area (ha)	451.64	150	727.93	63.15[§]
Share of rented land (%)	.62	.65	.22	.6181[§]
Workforce (*N*)	7.31	3	12.31	3.57[§]
Specialist crop farm (1 if yes, 0 otherwise)[†]	.27	0	.45	.3337[§]
Organic farm (1 if yes, 0 otherwise)	.18	0	.38	.0994[§]
Farmer's age (years)	48.23	50	10.77	55–64[§§]
Higher education (1 if yes, 0 otherwise)[‡]	.4	0	.49	.0925[§§]

Note: Number of observations = 624.

[†]Higher education refers to having a university degree. [‡]Destatis (2021b). [§]LfL (2015). [§§]Destatis (2021a)

result, the estimated β_n-coefficients are interpreted relative to the coefficient of the reference adaptation measure (Aizaki et al., 2014; Louviere et al., 2015; Lusk & Briggeman, 2009). Further details on the estimation procedure can be found in the Supplementary Materials S.3.

To obtain results that are consistent with standardized ratio scaling techniques and easy to interpret, the predicted probability of being chosen as the most preferred adaptation option by farmer n can be expressed as preference shares:

$$SP_{nj} = \frac{e^{\beta_{nj}}}{\sum_{k=1}^{J} e^{\beta_{nj}}} \tag{5}$$

where the preference shares assigned to each adaptation measure SP_{nj} reflect the preference for that adaptation measure, indicating the probability of favoring one measure over another. For example, if one adaptation measure scores twice as high as another, it means it is preferred twice as much. As preference shares are predicted probabilities, they must sum to one across all adaptation measures: $\sum_{j=1}^{13} SP_{nj} = 1$ (see Lusk & Briggeman, 2009; Ola & Menapace, 2020).

4 | RESULTS

4.1 | Sample characteristics

In total, 698 farmers participated in the survey. After conducting a series of plausibility and completeness checks, 624 responses were used for the analysis, which yielded a total sample size of 8112 farmer-choice observations (624 respondents multiplied by 13 choice sets each). The spatial distribution of the sample farms is depicted in Figure S2. The summary statistics for key farm characteristics are presented in Table 3 and are compared to the population means for Germany. It was found that due to the convenience sampling approach used (where only apprenticing farms were contacted), the farms in the sample tend to be larger and employ more workers than the average German farm. Additionally, the sample consists almost entirely of full-time farms. Farmers in the sample were found to be, on average, younger and better educated than the average German farmer. These deviations from the population mean are not necessarily a disadvantage, as they may indicate that the sample potentially represents a future-oriented and likely-to-survive farmer population, as described in Suess-Reyes and Fuetsch (2016).

More than 90% of the sample has experienced a change in climate, 59% found it has become harder to predict the weather, and 80% of farmers said that the number of extreme weather events on their farms has increased. Overall, 60% of the farmers experienced negative consequences from climate change on their farms, only 7% said they benefited from climate change, while 26% were not personally influenced by climate change. The most prominent adverse climate change impacts experienced by farmers were dry soils (90%), harvest losses (60%), and quality losses (30%).

In the BWS experiment, the surveyed farmers chose crop rotation diversification most often as the best measure (1284 times), followed by conservation tillage (995 times), the cultivation of cover crops, and the cultivation of resilient crops (both 854 times). Insurance was most often chosen as the worst measure (1927 times), followed by the use of irrigation (1485 times), and mixed cropping (990 times).

4.2 | Choice model results

Four versions of the mixed logit models were estimated following the theoretical considerations in Section 3.3. Insurance was chosen as the baseline because it was

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

ranked as the worst option most often. Therefore, all other coefficient estimates are interpreted relative to insurance. The estimation results are presented in Table 4, which demonstrates that all measures are significantly preferred to the insurance option independent of the chosen model.

Likelihood ratio tests confirm that the models considering correlation among the random coefficients fit the data statistically significant better than the uncorrelated models. The Akaike Information Criterion (AIC) as well as likelihood ratio tests indicate that environmental conditions have a significant impact on farmers' preferences for different climate change adaptation measures. Therefore, Model 4 was chosen as the preferred model because it accommodates both correlated coefficients and farmers' natural environment.

Table 5 describes the average preference shares (in %) based on the estimation results. Confidence intervals were calculated using the method by Krinsky and Robb (1986). On average and by a large margin, farmers assessed diversification of their crop rotation as the most preferred climate change adaptation measure, followed by conservation tillage, the use of cover crops, resilient crops, and crop varieties. Overall, the four most preferred measures made up more than 70% of farmers' preference shares on average. The four least preferred adaptation measures were insurance, irrigation, mixed cropping, and precision farming techniques. They jointly comprised less than 2% of farmers' preference shares.

Focusing on the preferred model (Model 4), it was observed that farmers were indifferent regarding several adaptation measures. For instance, on average, there were no statistically significant *ceteris paribus* differences between their preferences for the use of resilient crop varieties and the use of resilient crops.

The highly significant coefficient estimates of the standard deviations from the estimation results are indicative of the presence of considerable preference heterogeneity among farms (Table 4). This finding is further supported when looking at the farm-level preference results based on the individual-level coefficients from Model 4 (Figure 2).[3] Specifically, there was significant variability in both preference shares and rankings at the farm level. For example, the distribution of preference shares for adjusting crop rotation ranged widely, from under 10% to nearly 50%. Mixed cropping, for instance, fluctuated between being the fourth most favored to the second least favored adaptation measure.[4] Conversely, the analysis consistently revealed a widespread aversion towards insurance as a climate change adaptation measure, consistently ranking it very low (Figure 2).

4.3 | The impact of the natural environment on adaptation preferences

Given farmers' large preference variety for climate change adaptation, the we further explored the impact of climate and soil on their adaptation preferences. Figure 3 summarizes the preference shares (left panels) and rankings (right panels) of each climate change adaptation measure along the respective soil, temperature, and precipitation gradient (while holding the other two biophysical indicators constant at their mean values).

Figure 3a shows several distinct patterns regarding the influence of rainfall on climate change adaptation. First, the preference shares of the three most preferred measures in a dry environment (crop rotation diversification, conservation tillage, and the cultivation of resilient crops) decrease markedly as rainfall increases. Second, especially cover crops, the adjustment of farmers' management rhythms and mixed cropping gain importance as rainfall increases. These patterns are also reflected in the rankings of the measures, for example, the cultivation of resilient crops is ranked third under dry conditions but drops to rank seven under wet conditions. Similarly, conservation tillage drops from second to fifth. In contrast, cover crops are ranked five in a dry and number one in a wet environment, and mixed cropping goes up from 12 (dry) to four (wet). The results also show that farmers attach significantly more importance to irrigation under dry conditions than under wet conditions. Surprisingly, however, this adaptation measure remains relatively unimportant with a preference share of less than 1% independent of the rainfall conditions.

Figure 3b analyzes the influence of growing season temperature on adaptation preferences. Again, distinct patterns can be observed. For instance, diversifying one's crop rotation is by far and large the most preferred measure under cooler conditions with a preference share of 49%, which however drops to 18% under warmer conditions. There is a marked increase in the preference shares for the cultivation of resilient crops as well as the cultivation of resilient crop varieties as temperature rises. Overall, it can be observed that under cooler conditions very few adaptation measures dominate farmers' preferences while the preference shares are more equally distributed under warmer conditions.

Figure 3c evaluates the impact of soil quality (1 = low quality to 10 = high quality). Especially crop rotation diversification, business and income diversification, and the adjustment of management rhythms gain importance as soil quality improves. At the same time, the cultivation of resilient crops and crop varieties as well as cover crops and conservation tillage are considered very important in low soil quality settings and lose significance as soil quality rises. This has also a strong impact on the preference rank-

[3] Compare Equation (5).
[4] The preference ranking sorted adaptation measures according to their individual-level preference shares.

TABLE 4 Estimation results summary of mixed logit models.

	Model 1: No correlation, No environm. cond.	Model 2: Correlation, No environm. cond.	Model 3: No correlation, Environm. cond.	Model 4: Correlation, Environm. cond.
Precision farming	2.66 (.07)***	4.07 (.12)***	2.66 (.07)***	4.07 (.12)***
Adjustment of management rhythm	3.71 (.08)***	5.21 (.12)***	3.71 (.08)***	5.24 (.12)***
Adapted plant protection management	3.30 (.07)***	4.67 (.12)***	3.41 (.08)***	4.69 (.12)***
Adjustment of crop rotation	5.38 (.09)***	7.05 (.14)***	5.45 (.09)***	7.10 (.14)***
Conservation tillage	4.82 (.09)***	6.54 (.13)***	4.93 (.09)***	6.49 (.13)***
Adapted fertilization management	3.88 (.08)***	5.25 (.13)***	3.94 (.08)***	5.26 (.13)***
Cultivation of resilient crops	4.45 (.08)***	6.04 (.13)***	4.50 (.08)***	6.05 (.13)***
Cultivation of resilient crop varieties	4.48 (.08)***	6.03 (.13)***	4.55 (.08)***	6.04 (.13)***
Catch cropping	4.64 (.09)***	6.24 (.13)***	4.72 (.09)***	6.18 (.13)***
Mixed cropping	2.37 (.07)***	3.77 (.12)***	2.42 (.08)***	3.76 (.12)***
Irrigation	1.42 (.07)***	2.09 (.11)***	1.29 (.07)***	2.14 (.11)***
Business diversification	3.23 (.08)***	4.48 (.12)***	3.21 (.08)***	4.52 (.12)***
SD precision farming	1.93 (.07)***	4.04 (.14)***	1.94 (.07)***	4.04 (.14)***
SD adjustment of management rhythm	1.32 (.07)***	3.80 (.12)***	1.30 (.06)***	3.80 (.12)***
SD adapted plant protection management	1.92 (.07)***	4.40 (.14)***	1.96 (.07)***	4.40 (.14)***
SD adjustment of crop rotation	1.25 (.07)***	3.98 (.12)***	1.23 (.07)***	3.98 (.12)***
SD conservation tillage	1.56 (.07)***	3.94 (.13)***	1.56 (.07)***	3.94 (.13)***
SD adapted fertilization management	.96 (.07)***	3.70 (.13)***	1.02 (.07)***	3.70 (.13)***
SD Cultivation of resilient crops	1.05 (.07)***	4.21 (.13)***	1.11 (.07)***	4.21 (.13)***
SD cultivation of resilient crop varieties	.75 (.07)***	3.81 (.13)***	.78 (.07)***	3.81 (.13)***
SD catch cropping	1.18 (.07)***	3.59 (.12)***	1.13 (.07)***	3.59 (.12)***
SD mixed cropping	1.90 (.07)***	4.47 (.13)***	1.85 (.07)***	4.47 (.13)***
SD irrigation	2.55 (.08)***	4.07 (.12)***	2.41 (.08)***	4.07 (.12)***
SD business diversification	2.37 (.07)***	4.24 (.12)***	2.37 (.07)***	4.24 (.12)***
Precision farming : Temperature			−.17 (.11)	−.07 (.14)
Precision farming : Precipitation			−.17 (.05)**	−.17 (.07)**
Precision farming : Soil quality			−.08 (.12)	−.50 (.15)***
Adjustment of management rhythm : Temperature			−.28 (.11)*	−.18 (.14)
Adjustment of management rhythm : Precipitation			.04 (.05)	.16 (.07)*
Adjustment of management rhythm : Soil quality			.08 (.12)	−.14 (.15)
Adapted plant protection management : Temperature			−.29 (.11)*	−.05 (.14)
Adapted plant protection management : Precipitation			−.11 (.05)*	−.07 (.07)
Adapted plant protection management : Soil quality			−.21 (.12)$^{\circ}$	−.63 (.15)***
Adjustment of crop rotation : Temperature			−.45 (.12)***	−.39 (.15)**

(Continues)

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

TABLE 4 (Continued)

	Model 1: No correlation, No environm. cond.	Model 2: Correlation, No environm. cond.	Model 3: No correlation, Environm. cond.	Model 4: Correlation, Environm. cond.
Adjustment of crop rotation : Precipitation			−.02 (.05)	.06 (.07)
Adjustment of crop rotation : Soil quality			.03 (.12)	−.00 (.15)
Conservation tillage : Temperature			−.12 (.12)	−.07 (.15)
Conservation tillage : Precipitation			.05 (.06)	.00 (.07)
Conservation tillage : Soil quality			−.34 (.12)**	−.46 (.15)**
Adapted fertilization management : Temperature			−.18 (.12)	−.18 (.14)
Adapted fertilization management : Precipitation			.15 (.05)**	.12 (.07)°
Adapted fertilization management : Soil quality			−.16 (.12)	−.36 (.15)*
Cultivation of resilient crops : Temperature			−.23 (.11)*	−.09 (.14)
Cultivation of resilient crops : Precipitation			−.06 (.05)	.04 (.07)
Cultivation of resilient crops : Soil quality			−.50 (.12)***	−.59 (.15)***
Cultivation of resilient crop varieties : Temperature			−.16 (.11)	−.09 (.14)
Cultivation of resilient crop varieties : Precipitation			.07 (.05)	.14 (.07)*
Cultivation of resilient crop varieties : Soil quality			−.34 (.11)**	−.55 (.15)***
Catch cropping : Temperature			−.33 (.12)**	−.25 (.15)°
Catch cropping : Precipitation			.20 (.06)***	.26 (.07)***
Catch cropping : Soil quality			−.31 (.13)*	−.59 (.16)***
Mixed cropping : Temperature			−.09 (.11)	−.04 (.15)
Mixed cropping : Precipitation			.35 (.05)***	.44 (.07)***
Mixed cropping : Soil quality			−.32 (.12)**	−.81 (.15)***
Irrigation : Temperature			.57 (.12)***	.46 (.15)**
Irrigation : Precipitation			−.17 (.06)**	−.39 (.07)***
Irrigation : Soil quality			.36 (.12)**	.27 (.16)°
Business diversification : Temperature			−.10 (.12)	−.14 (.15)
Business diversification : Precipitation			−.12 (.06)*	−.03 (.07)
Business diversification : Soil quality			−.14 (.12)	.20 (.16)
Correlated random coefficients	No	Yes	No	Yes
Log likelihood	−13,750.35	−12,872.41	−13,644.56	−12,754.93
Akaike information criterion	27,548.69	25,924.81	27,409.12	25,761.86
Number of observations	8112.00	8112.00	8112.00	8112.00

Note: The mean coefficients indicate relative utilities, compared to the reference measure (insurance). The colon (:) in the description of the variables indicates the influence of environmental conditions (temperature, precipitation, and soil quality) on the mean of the random preference parameters (see Equation 4).
$^{***}P < .001$, $^{**}P < .01$, $^{*}P < .05$, $^{\circ}P < .1$.

TABLE 5 Average preference shares and associated preference ranking.

Adaptation measure	Preference share (%)	95% CI (%)	Rank
Diversify crop rotation	31.00	[27.83, 34.25]	1
Conservation tillage	16.91	[15.31, 18.57]	2
Use of catch crops	12.43	[10.90, 14.05]	3
Use of drought-resistant crops	10.91	[9.74, 12.15]	4
Use of drought-resistant crop varieties	10.83	[9.54, 12.17]	5
Adjust fertilization	4.95	[4.27, 5.68]	6
Adjust management rhythm	4.87	[3.73, 6.20]	7
Adjustment of farm chemicals use	2.79	[2.44, 3.16]	8
Business diversification	2.36	[1.98, 2.78]	9
Use of precision farming	1.61	[.71, 3.11]	10
Use of mixed crops	1.10	[.90, 1.33]	11
Use of irrigation	.22	[.17, .28]	12
Insurance	.03	[.02, .03]	13

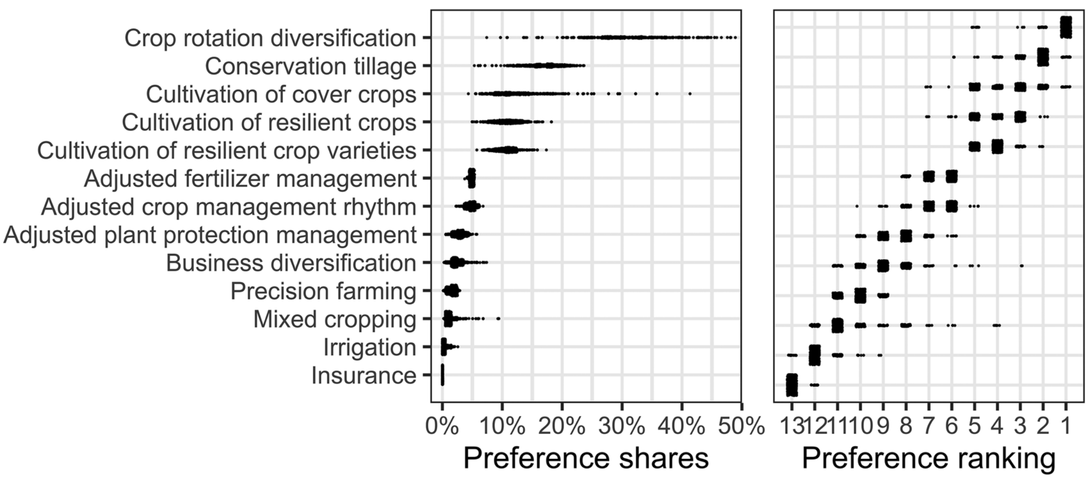

FIGURE 2 Preference shares and rankings of each climate change adaptation measure evaluated for each farm in the sample.

ings. For instance, the cultivation of cover crops drops from rank one (bad soil conditions) to rank five (good soil conditions) and the cultivation of resilient crops from three to seven. Simultaneously, business and income diversification increases from rank eleven to rank three, adjusting one's management rhythm increases from rank ten (low soil quality) to rank four (high soil quality), and crop rotation diversification increases from rank five to one.

In general, natural conditions are strongly associated with farmers' relative preferences for climate change adaptation measures. At the same time, farmers appear to assign relatively low importance to several adaptation measures, namely insurance, irrigation, and precision farming.

Lastly, the relationship between the interaction of environmental conditions and farmers' adaptation preferences was assessed (Figure 4). Distinct patterns can be found; for example, cover crops appear to be particularly relevant under high precipitation and low-temperature conditions as well as in low soil quality and high precipitation environments. Additionally, the cultivation of resilient crops appears to be especially attractive in dry and hot settings as well as in dry, warm, and low-soil-quality settings. A similar pattern can also be found for conservation tillage. Although diversifying crop rotation is generally ranked as important to farmers, its relevance to farmers increases in cold–dry, cold–good soil, and dry–good soil situations.

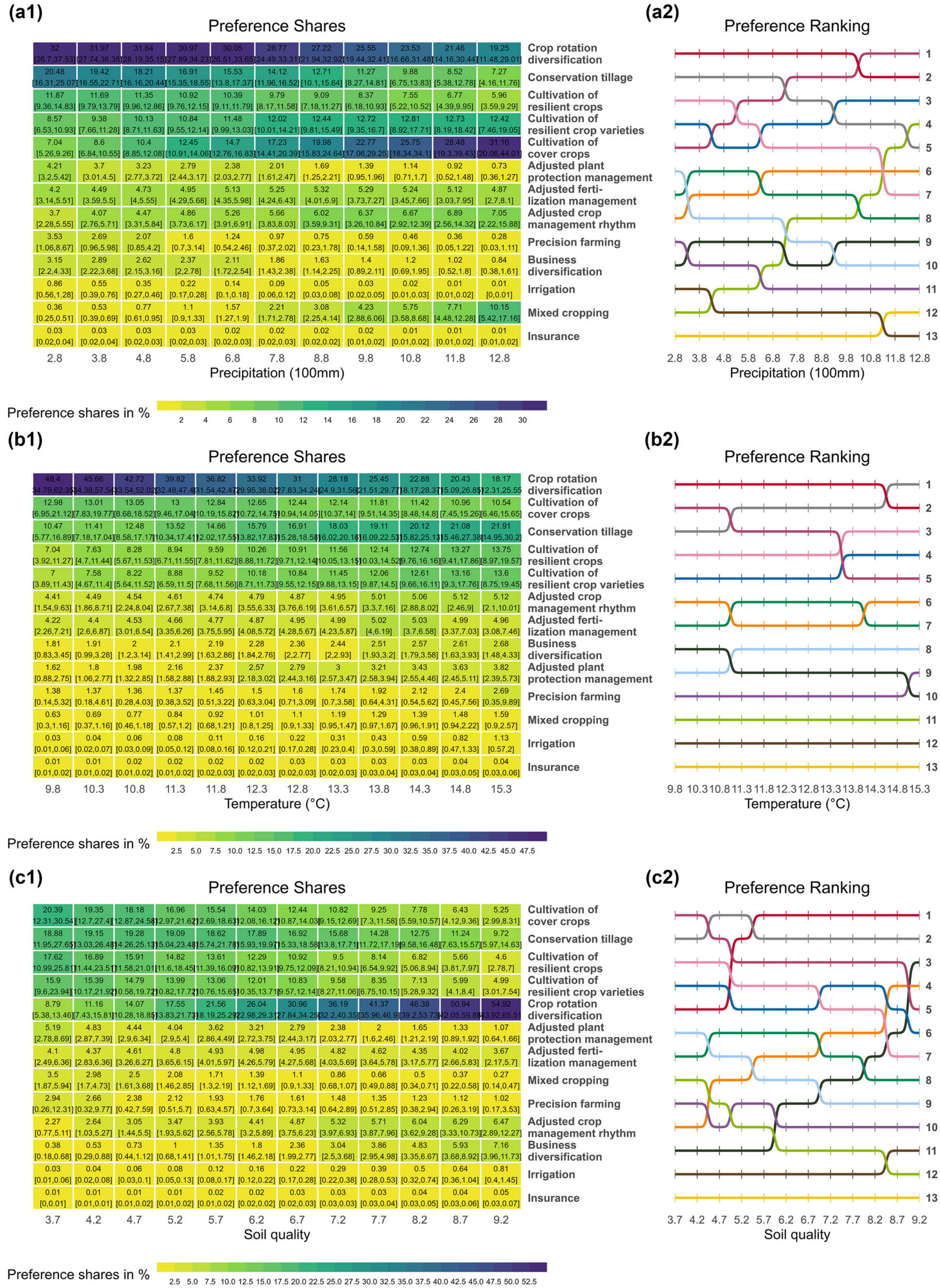

FIGURE 3 Preference shares (95% confidence intervals in brackets, left panels) and corresponding preference rankings (right panels) of each climate change adaptation measure along the precipitation and temperature normals (1991–2020) and soil quality.

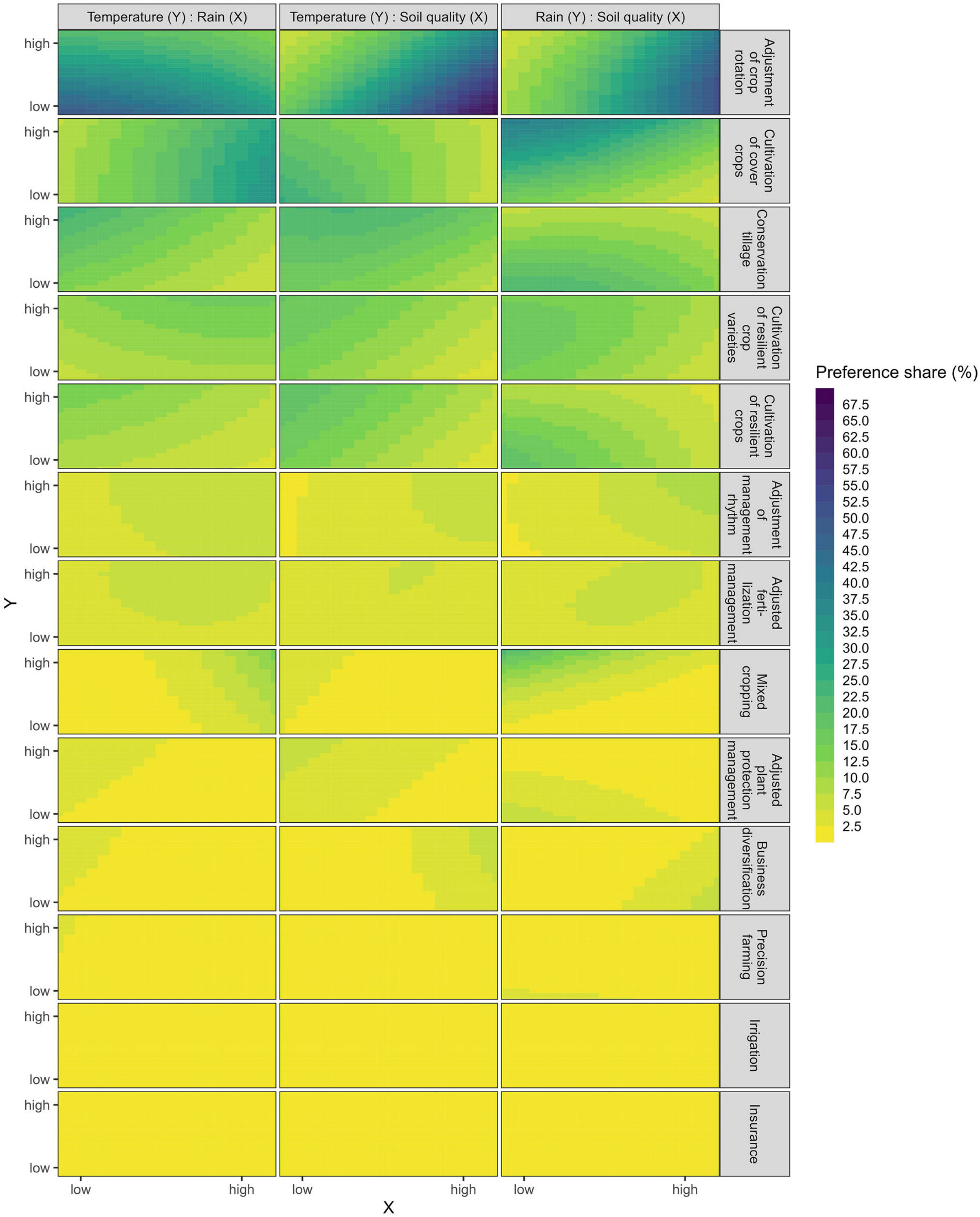

FIGURE 4 Interaction effects of environmental conditions on farmers' preference shares (while holding the other biophysical indicator constant at its mean value).

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

5 | DISCUSSION

5.1 | Farmers' preferences for climate change adaptation

Climate change poses significant challenges to German crop farming. Several studies indicate a future decrease in water availability and a rise in temperatures, which could potentially result in lower yields of important crops like winter wheat or silage maize (Gornott & Wechsung, 2016; Lüttger & Feike, 2018). These findings highlight the need for German crop farmers to implement adaptation measures to maintain agricultural productivity, sustainability, and resilience in the face of changing environmental conditions.

The results show that there is a tendency for farmers in GermGery to prioritize, on erage, gradual, mostly agronomic adaptation measures. This is in line with Woods et al. (2017), who also found that farmers (in Denmark) are more likely to make adjustments that are gradual and allow for flexibility. Farmers' preferences for adaptation measures also vary depending on the conditions of temperature, precipitation, and soil quality at the farm location. Other studies support this by showing that adaptation in response to climate change varies by geography, cropping systems, topography and soils, and local experience with climate and weather (Stetter & Sauer 2024; Walthall et al., 2012; Wimmer et al., 2024). At this point, it is essential to clarify that this analysis does not aim to predict specific adaptation measures at the local level. Rather, the focus is on understanding the variation in preference scores associated with local environmental conditions. This distinction is crucial to avoid any confusion regarding the scope and applicability of the findings. Apart from the variables examined in this study, climate and soil conditions, it is important to acknowledge the influence of other factors on farmers' choice of adaptation measures. Behavioral traits, such as risk attitude and perception of climate change, play a significant role in shaping farmers' decision-making processes (Dessart et al., 2019). Additionally, farm characteristics such as farm size, production focus, and available resources as well as socioeconomic attributes of farmers, including age and education, can further shape their adaptation measures (see e.g., Benitez-Altuna et al., 2021; Blasch et al., 2022; Wang et al., 2023). Therefore, these findings represent only one dimension of a complex, multifaceted phenomenon and should be interpreted as such.

In this case study, the most preferred adaptation measure was the adjustment of crop rotation (i.e., diversification). This measure is considered highly flexible (Dolan et al., 2001), as it can be relatively easily modified to accommodate changing climatic conditions. von Czettritz et al. (2023) show that the diversification of crop rotation plays a vital role for climate-resilient agricultural production in the state of Brandenburg (Germany), contributing most significantly to economic resilience in regions with moderate to low productivity. Hart et al. (2012) also evaluate this measure for the EU and classify it as an at least moderately effective adaptation measure, as it reduces runoff and erosion, increases organic matter and carbon sequestration, improves soil quality, and provides benefits for pest control and better moisture utilization. However, the results also show that the soil quality is an important determinant for farmers to use this adaptation measure.

Conservation tillage, the second-highest ranked adaptation measure on average, is evaluated to have a highly positive effect on the resilience of farm-level production regarding climate risk. It is a no-regret measure that is assessed to be an effective measure in the EU under medium to high climate scenarios (Hart et al., 2012). The farmers in this sample consider this measure particularly relevant in dry settings, which is supported by a study from Morton et al. (2017), where farmers who experienced drought in the upper Midwest in the U.S. were more likely to use soil management practices.

The cultivation of cover crops is generally regarded as moderately beneficial for climate change adaptation (BMEL, 2020; LFULG, 2009) as cover crops can potentially intensify competition for the use of water in arid areas and reduce adaptive capacity by preventing the establishment of cash crops (Kaye & Quemada, 2017). Farmers appear to acknowledge this as they consider this measure particularly important under wetter conditions compared to dry conditions. However, using cover crops during winter can reduce nutrient run-off and leaching, as well as erosion caused by storms, flooding, or flash floods (Hart et al., 2012).

As for the cultivation of resilient crops (and crop varieties), tolerance to drought stress, rising CO_2 concentrations and the growing prevalence of pests are becoming increasingly important when deciding which crops to grow (Wehner et al., 2017). Cultivating resilient crops and crop varieties is considered an effective measure under low to medium climate change scenarios (Hart et al., 2012). Farmers generally attach greater importance to these measures under warm, dry, and low soil quality conditions. Results of a choice experiment conducted by Zander et al. (2023) with German wheat farmers indicate that farmers preferred disease-resistant varieties with traits of yield stability (e.g., fungal disease resistance or drought tolerance) over higher yield potentials. Notably, choices were also based on a combination of factors like the production system, drought experience, and climate change beliefs. However, on a global level rapid-cycle breeding that delivers a steady stream of incrementally improved cultivars will be necessary to ensure successful adaptation (Atlin et al., 2017).

In general, the above-discussed measures all relate to crop management. The preference for these adaptation measures might be due to several reasons, such as the provision of co-benefits. For instance, conservation tillage is able to increase the soil organic carbon content, limit nutrient leaching, decrease soil compaction, improve soil aeration and soil water relations, increase soil porosity, improve soil structure, and enhance microbial as well as enzymatic activity in the soil (Wanic et al., 2019). These measures have mostly low implementation costs, making them no- to low-regret measures for farmers (Hart et al., 2012). However, multiple studies found that these crop management measures are severely limited in their efficacy in tackling the increasingly severe impacts of climate change on farms (Chhetri et al., 2010; Hunter et al., 2021; Ishtiaque, 2023; Ko et al., 2012; Malek et al., 2020).

Given our results, German farmers seem to be hesitant with respect to more transformative adaptation measures. Transformative adaptation measures such as farm and income diversification, mixed cropping, or investment in irrigation are less favored than relatively easy-to-implement adaptation measures in the area of farm management and crop production (see above), although these measures may be more effective in terms of climate change adaptation (e.g., Mey et al., 2016). The skepticism of farmers toward these more effective adaptation measures may be attributed to a variety of factors, including a lack of information, technical barriers, high costs, unfavorable market conditions, and the political framework.

For example, Himanen et al. (2016) highlight that mixed cropping, despite its several benefits (de Bruin et al., 2009), presents significant challenges. These include a lack of information on plant variety performance and optimal yields in mixtures, industry and policy requirements for seed purity, more complex management and harvesting, and the economic risks associated with experimenting with novel mixtures. However, farmers appeared to attribute a higher relevance to this adaptation measure under wetter conditions.

Although irrigation plays an important role as a climate change adaptation measure in countries like the U.S. (Ishtiaque, 2023), German farmers in this sample attribute little relevance to this measure (although more preferred under dry circumstances). The use of irrigation for crops in the case study region is likely hampered due to stringent regulation of agricultural water use by a large number of laws, ordinances, and administrative regulations. On top of that, irrigation of other agricultural crops has only been profitable in a few dry locations so far due to high implementation costs (Schimmelpfennig et al., 2018).

Business and income diversification were also perceived as rather irrelevant in most situations although they can be a self-insurance measure used by farmers to safeguard against (climate) risks (Mishra et al., 2004; Wuepper et al., 2018; van Zonneveld et al., 2020). Jack et al. (2021) discuss potential barriers to farm diversification including government regulations, the lack of secure planning permission, high legislative and regulatory requirements, lack of entrepreneurship, lack of confidence, lack of training, and peer pressure. These factors could potentially also have an influence in this study's setting.

Precision farming was not favored by the farmers in the study. This could be because its connection to climate change is less clear compared to other measures, making it seem less relevant. But it could also be that farmers do not perceive precision farming to be effective, which has also been shown in the literature (e.g., Chhetri et al., 2010).

Finally, insurance was consistently ranked as the least important measure, despite the fact that weather risk insurance can contribute greatly to the three resilience capabilities of agriculture, namely robustness, adaptability, and transformative capacity (Meuwissen et al., 2019; Spiegel et al., 2020). Insurance does not only compensate for damage but offers premiums to adapt and motivate behavioral changes (Cimato & Mullan, 2010; Vroege et al., 2021). By spreading the risk or transferring the risk to a third party, insurance can cushion the financial effects of an unexpected crop failure after extreme events such as hail or drought (Di Falco et al., 2014). One reason farmers may rate insurance solutions low could be that they often associate climate change with specific hazards, particularly drought, which is a leading cause of crop yield losses and significant financial setbacks (Bucheli et al., 2021). At the same time, there are only very few insurance solutions available against drought risks (Bucheli et al., 2023), which might cause farmers to neglect this as an effective measure against climate change impacts.

In summary, there appears to be a preference for low-cost, easy-to-implement measures over more expensive, transformative ones, consistent with the findings of Fagariba et al. (2018). The results also imply a discrepancy between farmers' preferences for climate change adaptation measures and the actual effectiveness of these measures. Closing this gap will be key to successful adaptation to climate change at the farm level. The study also shows that preferences for adaptation measures depend on environmental conditions at the farm level. Therefore, understanding the local determinants of adaptation preferences is crucial for the design and implementation of successful interventions, including climate change adaptation programs. Although the findings of this study refer to German agriculture, the results are likely applicable to other European farming regions with similar conditions.

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

5.2 | Policy implications

Given that arable crop farmers' preferences are highly heterogeneous and context-specific in this study, it is crucial to recognize that there is no one-size-fits-all solution regarding climate change adaptation (Hansen & Bi, 2017). Policymakers need to tailor their approaches to align them with the specific preferences and circumstances of farmers. In order to address the misalignment between farmers' preferred measures and the most effective measures for climate change adaptation, it is crucial for policymakers to have a thorough understanding of farmers' adaptation preferences. There are a number of ways in which policymakers can align policies with farmers' context-specific preferences. One important step is to consult with farmers and other stakeholders during the policy development process (compare e.g., van Dijk et al., 2017; Vayssières et al., 2011). This could help policymakers to understand farmers' needs and concerns, and to develop policies that are more likely to be adopted and effective.

Another important step is to provide farmers with information and resources about the benefits of different adaptation measures in the context of their biophysical environment (Di Falco et al., 2011; Mulwa et al., 2017). Promoting these practices through extension services and financial incentives encourages adoption while considering local circumstances (compare McNeeley, 2017; Silva et al., 2021). In addition to local services, policymakers should adopt flexible policies that accommodate diverse farmer and regional needs, acknowledging the spatial and temporal variability of climate change (see e.g., Schlenker & Roberts, 2009).

Next, taking a systemic approach, it is crucial to focus on agricultural institutions, including government agencies and extension services, as they significantly influence policy implementation (Islam & Nursey-Bray, 2017). They control the allocation of critical resources such as funding, technology, and training, which must be aligned with farmers' preferences to enable better decision-making and prevent legislators from being "out of touch" with farmers' needs and preferences (Crane et al., 2011).

Low-regret or no-regret adaptation measures, like adjustment of crop rotation, conservation tillage, catch cropping, cultivation of resistant crops, cultivation of resistant varieties and mixed cropping, should be implemented into policy frameworks disregarding climate change (Abildtrup et al., 2001). These measures could be further encouraged through, for example, incentive-based policy instruments, like the agri-environmental funding programs of the states in Germany (Zinngrebe et al., 2017). One of the major barriers to the adoption of effective adaptation measures is cost. For instance, irrigation technologies can be costly for farmers to implement (e.g., Spaeti et al., 2021). The results of this study show that the measures precision farming, irrigation technology, and insurance are three of the four least preferred measures, although they are among the most effective. Precision farming techniques or irrigation technologies are adaptation measures that aim at saving resources and should therefore be given priority for implementation into policy frameworks (Abildtrup et al., 2001; Moriondo et al., 2010). To address this, policymakers could support the development and implementation of cost-effective, open-source solutions that are easy and intuitive to use (Kpienbaareh et al., 2019). This could make the adoption of these technologies more attractive for many farmers (Hansjürgens et al., 2017; Häußler et al., 2020). Additionally, policymakers could reallocate public funds to counteract the low preference for these measures due to their high costs.

There are other external factors that can influence farmers' preferences as well, such as market conditions (Himanen et al., 2016). Research indicates that farmers may feel constrained in their cultivation choices due to underdeveloped or inflexible market structures, which can hinder their ability to transition to more diverse farming systems (Roesch-McNally et al., 2018). For example, introducing new or lesser-known varieties of crops can be difficult if the market is not aware of their benefits (Nuijten et al., 2018; Tamm et al., 2004; Vanloqueren & Baret, 2008; Weibel et al., 2013). Policymakers should take these factors into consideration when developing and promoting adaptation measures, and work to address the barriers that limit farmers' options by promoting awareness of sustainable and climate-resilient practices among retailers, consumers, and traders, and supporting farmers in identifying and accessing new markets (Nuijten et al., 2018; Scherer & Verburg, 2017).

5.3 | Limitations

It is important to note certain limitations of this study. First, the sample of this study was geographically restricted to Germany, and due to the convenience sampling approach used, it may not be representative of all German arable farmers. Therefore, caution should be exercised when attempting to generalize the findings to other contexts and regions. Additionally, while every effort was made to provide comprehensive descriptions of the adaptation measures, it is possible that farmers' perceptions of the adaptation practices may have differed from the understanding of the researchers, which could have influenced the results of the BWS method used in the study. This method, while offering many advantages over other rating techniques, does not provide any information about the attractiveness of the scenario in relation to the current position of the respondent.

Adaptation measures are rarely implemented in isolation, and evaluating combinations of measures may yield different preference scores. Although correlation among measures in the econometric model was allowed for, the chosen BWS approach does not allow for a detailed assessment of farmers' preferences with respect to adaptation bundles.[5] Focusing on individual adaptation measures in the study may therefore overlook the synergistic effects that arise from combining multiple measures.

Lastly, the production environment of farmers was defined by their environmental conditions. Although alternative specifications that focused on the influence of behavioral characteristics of farmers on their climate change adaptation measures were rejected in favor of our model specification, more research is needed to study the influence of these factors on climate change adaptation. These limitations should be taken into account when interpreting the results of this study.

6 | CONCLUSION

With the pressing rate and intensity of climate change, understanding how farmers evaluate and prioritize among multiple available adaptation measures is key for successful implementation. This study explores farmer preferences of climate change adaptation measures and their relationship to local climatic and soil conditions. It determined the relative importance that German arable farmers attribute to different adaptation measures using a best-worst scaling experiment and explored its heterogeneity under various environmental conditions.

In total 13 adaptation measures were evaluated. The findings of the mixed logit model showed that, on average, farmers assigned the highest importance to the diversification of their crop rotation, followed by conservation tillage methods, the use of cover crops, as well as the use of resilient crops and crop varieties. The least preferred adaptation measures were insurance, the use of irrigation, the use of mixed crops and precision farming techniques. Preferences varied considerably along the temperature, precipitation and soil gradients. Overall, the results suggest a general tendency that farmers preferred agronomic, low-cost adaptation measures that are not necessarily the most effective ones. This study highlighted multiple leverage points for policymakers to improve this situation. Overall, neglecting farmers' preferences and needs regarding climate change adaptation can potentially lead to suboptimal policy outcomes.

To conclude, potential directions for future research are highlighted. While the study delineates adaptation measures based on environmental conditions, further research is warranted to explore the impact of farmers' behavioral characteristics on climate change adaptation. What is more, it would be worthwhile to see similar studies in other contexts with different farming structures, farming conditions, and production systems. It would also be interesting to further analyze the interplay between preferences and adoption and evaluate how preferences for specific climate change adaptation measures translate to adoption. Finally, to gain a more comprehensive understanding of climate change adaptation, further research is needed to evaluate measure bundles in different contexts.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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[5] As a first tentative attempt to get insights into the issue, correlations among the preference shares of the individual adaptation measures were calculated (see Supplementary Material).

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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