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ARTICLE

Farm-level responses to weather trends: A structural model

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Abstract
Assessing the effects of weather and climate on agricultural production is crucial for designing policies related to climate change adaptation and mitigation. A large body of literature has identified the detrimental effects of climate change on crop yields worldwide, and farm-level adaptation has been shown to mitigate the adverse effects on agricultural production. In this study, we employ a structural model to examine farm production responses to ongoing weather trends. We investigate how farmers adjust output and input decisions by estimating a system of output supply and input demand functions, controlling for nonrandom crop selection. Using panel data with 14,796 observations reflecting 1638 German crop farms (1996–2019), we find that both the expected and realized weather determine farmers' production decisions. In the event of a drought, the supply of most considered crops and the demand for fertilizer decrease. The drought shock has also lasting effects on farmers' production decisions, with a reduced supply of protein crops and an increased level of root crops production in subsequent years. These findings highlight the need to account for farm-level production responses when assessing weather and climate impacts.

KEYWORDS
agriculture, crop farms, drought, farm-level adaptation, production decisions, profit function, structural model, weather

JEL CLASSIFICATION
Q12, Q54

1 | INTRODUCTION

Agricultural production is inherently related to weather (Ray et al., 2015). Rising mean temperatures, along with changing precipitation patterns, have substantially altered the growing conditions of crops (Lobell et al., 2011) and livestock (Gisbert-Queral et al., 2021). Globally, anthropogenic climate change has already caused significant losses in agricultural productivity (Ortiz-Bobea et al., 2021). The increasing frequency of extreme weather events, such as floods, droughts, or frost, poses an additional threat to agricultural production (e.g., Barlow et al., 2015; Pullens et al., 2019; Schmitt et al., 2022; Trnka et al., 2014) and hence to food supply and quality (Dalhaus et al., 2020). The ability of farms to adjust to these environmental changes is crucial for the future viability and resilience of the agricultural sector. The analysis of farmers' revealed adaptation and production decisions allows us to understand their responses to (extreme) weather events, supporting the development of targeted policies to support their adaptation to climate change.

This study examines farm production responses to weather trends. The primary goal is to quantify changes in output supply and input demand in response to changes in expected and realized weather, taking into account reactions at both the extensive and intensive margins. For this purpose, we formulate a profit maximization problem in which farmers decide on planned output and input levels depending on their weather expectations. During the cropping season, they respond to contemporaneous weather outcomes by adjusting variable inputs such as fertilizers. Based on the theoretical framework, we estimate the farms' optimal output supply and input demand functions conditioned on economic and environmental variables. We then use the estimated parameters to simulate the immediate and lasting effects of a drought shock on farmers' input and output choices. Our case study relies on detailed panel data with 14,796 observations reflecting 1638 German crop farms (1996–2019), matched with local weather data.

Previous studies on the impact of weather and climate on agricultural production have often relied on large-scale modeling approaches (e.g., Agnolucci et al., 2020; Rosenzweig & Parry, 1994; Webber et al., 2018) or statistical models using either panel data methods (Deschênes & Greenstone, 2007; Schlenker & Roberts, 2009) or cross-sectional methods (Mendelsohn et al., 1994). It has been argued that panel data models are limited in their capability to capture long-term adjustments, which may overestimate the impact of climate change (e.g., Carter et al., 2018; Mérel & Gammans, 2021).[1] The Ricardian approach, on the contrary, was designed to account for long-run adjustments to different climates by exploiting cross-sectional variations in climatic conditions and economic farm returns but is more vulnerable to omitted variable bias (Carter et al., 2018; Ortiz-Bobea, 2020). Recent applications include those of Bozzola et al. (2018), Ortiz-Bobea (2020), Huang and Sim (2021), and Bareille and Chakir (2023).

Neither of the mentioned approaches reveals how farmers adjust their production to different climatic conditions. For example, farmers may adjust the level of fertilizer use in the short run or replace heat-sensitive crops under global warming (Reidsma et al., 2010). One merit of structural models in this context is that they retain the parameter estimates that describe the farmers' decision-making processes. Contrary to reduced-form models focusing on the weather-yield relationship for specific crops, our structural model is formulated at the individual farm-level as the decision-making unit and thus allows for identifying trade-offs in the supply of different crops, which arise from farmers' optimal resource allocation given the expected and realized weather outcomes. In the context of climate change, only few applications of structural models exist (e.g., Kaminski et al., 2013; Kan et al., 2023; Sesmero et al., 2018; Yang & Richard Shumway, 2016).

We contribute to this literature and to the understanding of weather and climate impacts on agriculture in at least three ways. First, we assess how ongoing weather trends affect farmers' input demand and output supply by incorporating both realized weather and weather expectations into a

[1]Recently, panel data models have also been applied to examine farm-level adaptation strategies (e.g., Cui & Xie, 2022 on growing season adjustments, or Li, 2023 on reallocation of land and irrigation water).

profit function. Li (2023) have investigated farm-level adaptation to expected and unexpected weather fluctuations using several reduced-form estimations. Following recent qualitative (Wilke & Morton, 2017) and quantitative (Ramsey et al., 2021) evidence, we assume that farmers form weather expectations by distinguishing between the more recent and the more distant pasts. Although Ramsey et al. (2021) have used this approach to estimate crop choices at the field level, this study is the first to integrate it into the estimation of output supply and input demand functions derived from a structural profit maximization model. This allows us to provide novel insights into how the behavioral aspects of farmers' weather expectations besides weather realizations affect output supply at the crop level, as well as input demand, in a unified framework.

Second, we use the estimated parameters of the output supply and input demand functions to simulate farmers' output supply and input demand responses to a weather shock and examine potential farm heterogeneity in weather responses, which is largely underexplored in the existing literature. In this context, our study also complements previous literature that used structural models to investigate long-term climatic effects on output and input choices (e.g., Kaminski et al., 2013; Sesmero et al., 2018; Yang & Richard Shumway, 2016) by providing empirical evidence on farm-level responses to weather shocks in the short and medium terms. Understanding these effects is particularly important given the current and future exposure of agriculture to weather shocks (e.g., Webber et al., 2018).

Third, we use farm-level data and disaggregated crop categories (cereals, protein crops, oilseeds, root crops, and corn), which offers detailed insights into the decision-making processes of farmers and facilitates the analysis of heterogeneous responses to weather trends that would be masked in aggregated data. The aforementioned structural models in the weather and climate literature rely on regional data (Kaminski et al., 2013; Kan et al., 2023; Yang & Richard Shumway, 2016) or use a higher aggregation level for outputs, such as maize and non-maize crops (Sesmero et al., 2018) or crops and livestock output (Yang & Richard Shumway, 2016). The use of farm-level data and disaggregated crop categories result in corner solutions, because not all farms grow all of the considered crops, which can bias the estimation results. We address this issue econometrically using a two-stage regression framework that accounts for farmers' nonrandom crop selection in response to previously observed weather outcomes.

We find that both observed and expected weather, formed based on weather experienced in the past, affect the output supply and input demand, and that these effects vary across crops. For example, increasing the number of growing degree days decreases cereals supply but increases root crops supply, ceteris paribus. By simulating the immediate and lasting effects of a drought shock on farmers' production decisions, we find that corn supply declines the most in the year of the shock, along with a reduction in fertilizer usage. Although the supply of protein crops, corn, and oilseeds is particularly reduced in the years after the shock, fertilizer demand and cereals supply quickly return to their original levels, and roots crop supply tends to increase in subsequent years. Additionally, we find heterogeneous responses across farm sizes, with smaller farms being affected more by the drought shock than larger farms. These results hold under various robustness checks, that is, using either linear or nonlinear weather effects and imposing regularity conditions on the profit function.

The remainder of this paper is organized as follows. The conceptual framework introduces farmers' decision-making processes in the context of expected and realized weather outcomes. The next section describes the econometric framework, including nonrandom crop selection and the simulation exercise, before farm and weather data are introduced. Subsequently, the results are presented and discussed, and the final section concludes with implications for policy and future research.

2 | CONCEPTUAL FRAMEWORK

The study aims to assess farmers' input and output decisions in response to local weather trends, taking into account extensive and intensive margin adjustments. Naturally, the relationship between weather and agricultural yields is crop specific. For example, sugar beets and potatoes require high precipitation and cannot be grown in dry regions without irrigation (Döll & Siebert, 2002; Siebert et al., 2013). Precipitation is also a limiting factor for winter wheat, whereas temperature is considered a limiting factor for corn and sugar beet production in Germany (Lotze-Campen et al., 2009). Cachorro et al. (2018) find that rising temperatures negatively affect summer crop yields, especially sugar beets and potatoes. Crop models by Agnolucci et al. (2020) predict that increasing temperatures in Germany benefit canola yields but reduce the yield of pulses. Considering extreme weather events, Webber et al. (2020) found that drought is an important driver of yield losses in corn for silage and, to a lesser extent, barley and wheat in eastern Germany. In the same study, heat is found to have negative effects on wheat yields, whereas canola and corn for silage are less affected by unusually high temperatures.

However, to assess the effects on total production, it is important to look beyond pure weather-yield effects and consider farmers' responses to local weather trends. The effect of weather on farmers' production decisions depends not only on individual yield effects but also on the relative profitability of each crop under different weather conditions. For example, if one crop suffers more from dry conditions than another, it may be rational to allocate more resources to the less-affected crop. Furthermore, experiencing a weather shock may alter farmers' weather expectations, which in turn affects optimal production choices not only in the year of the shock but also in subsequent years. Hence, accounting for farmers' behavioral responses (and the heterogeneity therein) to weather trends and shocks is important for assessing the role of weather trends and shocks on agricultural production. Additionally, agronomic aspects of crop rotation affect the adjustment of crop portfolios. Thus, farmers' production responses to changing weather patterns are difficult to assess a priori and remain empirical questions.

2.1 | Weather and production decisions

Following Chambers and Just (1989), we model farmers' decision making process at the beginning of the crop season in two stages, assuming risk-neutral decision makers. In the first stage, farmers maximize the expected profit from each crop given the allocations of fixed resources. The corresponding crop-specific profit function is expressed as

$$E\left[\pi_c\left(E\left[p_c\right],\boldsymbol{r},\boldsymbol{z_c},\boldsymbol{s},E[\boldsymbol{w}]\right)\right]=\max_{\boldsymbol{x_c},E\left[q_c\right]}\left(E\left[p_c\right]E\left[q_c\right]-\boldsymbol{r}'\boldsymbol{x_c}:E\left[q_c\right]\in Q^c(\boldsymbol{x_c},\boldsymbol{z_c},\boldsymbol{s},E[\boldsymbol{w}])\right), \tag{1}$$

where $E[\pi_c]$ is the expected maximum profit from producing crop c, $E\left[p_c\right]$ is the expected price for crop c, $\boldsymbol{r}$ is a vector of variable input prices, $\boldsymbol{x}_c$ is a vector of variable inputs used for the production of crop c, $\boldsymbol{z}_c$ is a vector of fixed but allocatable inputs used for the production of crop c, $\boldsymbol{s}$ is a vector of site-specific characteristics, and $E[\boldsymbol{w}]$ is a vector of expected weather outcomes. The technology constraint ensures that the production plan for producing the expected output $E\left[q_c\right]$ is feasible, given, for instance, the expected weather conditions as denoted by technology $Q^c(\cdot)$. In the second stage, the allocatable fixed inputs are allocated across individual crops to maximize the expected total profit. The multicrop profit function for producing C crops is defined as

$$E[\pi(E[\boldsymbol{p}],\boldsymbol{r},\boldsymbol{z},\boldsymbol{s},E[\boldsymbol{w}])]=\max_{\boldsymbol{x},E[\boldsymbol{q}]}\left(\sum_{c=1}^{C}\left(E\left[p_c\right]E\left[q_c\right]\right)-\boldsymbol{r}'\boldsymbol{x}\;:\;E[\boldsymbol{q}]\in Q(\boldsymbol{x},\boldsymbol{z},\boldsymbol{s},E[\boldsymbol{w}])\right). \tag{2}$$

According to standard results, the well-behaved profit function is nondecreasing in output prices, nonincreasing in input prices, and linearly homogeneous and convex in prices (Chambers, 1988). The optimal allocation of allocatable fixed inputs (e.g., land or labor) made at the beginning of the crop season depends on the expected weather, because weather affects the profitability of each individual crop, as shown by $Q^c(\cdot)$ in Equation (1).

During the crop season, farmers can adjust variable inputs (e.g., fertilizers) in response to actual weather realizations.[2] Hence, if the realized weather deviates from the expected weather, the observed input use can deviate from the assumed input use at the beginning of the season. Moreover, planned output levels may be adjusted, because it is economically rational to allocate more resources to crops for which the realized weather conditions are the most favorable. In addition, realized output levels can of course deviate from planned output levels through the direct effects of realized weather on crop yields, and this direct response can depend on past weather by influencing past adaptations. For example, a farmer in a generally dry region may be better prepared for another drought than one in a generally wetter region (Dell et al., 2014; Mérel & Gammans, 2021; Schlenker et al., 2013).

For these reasons, and following Sesmero et al. (2018), we express the farms' profit as a function of both expected and realized weather:

$$\pi = f(E[\boldsymbol{p}], \boldsymbol{r}, \boldsymbol{z}, \boldsymbol{s}, E[\boldsymbol{w}], \boldsymbol{w}) \tag{3}$$

The primary goal of this study is to evaluate farmers' responses to weather trends in terms of output supply and input demand. Having specified the profit function in (3), we can derive the farms' profit-maximizing output supply functions for each crop c and input demand functions for each input k by taking the first derivatives with respect to the output and input prices (Hotelling, 1932):

$$q_c = \frac{\partial f(E[\boldsymbol{p}], \boldsymbol{r}, \boldsymbol{z}, \boldsymbol{s}, E[\boldsymbol{w}], \boldsymbol{w})}{\partial p_c}, -x_k = \frac{\partial f(E[\boldsymbol{p}_c], \boldsymbol{r}, \boldsymbol{z}, \boldsymbol{s}, E[\boldsymbol{w}], \boldsymbol{w})}{\partial r_k} \tag{4}$$

We use the output supply and input demand functions in (4) to empirically assess farmers' responses to expected weather $E[\boldsymbol{w}]$ while controlling for realized weather $\boldsymbol{w}$. Their functional forms depend on the assumed functional form of the profit function. To account for past adaptation decisions as explained above, we follow Dell et al. (2014) and include a multiplicative interaction term between past weather and realized weather in the empirical estimation to ensure that the marginal effects of experienced weather on output supply and input demand are functions of past weather.

In summary, the described decision-making process highlights that weather affects farmers' production decisions at the extensive and intensive margins through two channels. The first channel is through the adjustment of allocatable fixed inputs based on farmers' weather expectations, which carry a behavioral component and define the expected profitability of individual crops. The second channel is the direct influence of the observed weather on yields while allowing for short-term input adjustments during the crop season and past adaptation decisions.

2.2 | Formation of weather expectations

Following Ramsey et al. (2021), we express the farmers' expectations for the j-th weather variable as

$$E[w_{jit}] = \omega_0 + \omega_s W(w_{ji,t-1}, w_{ji,t-2}, \dots, w_{ji,t-T^*}) + \omega_l W(w_{ji,t-T^*-1}, w_{ji,t-T^*-2}, \dots, w_{ji,t-T}), \tag{5}$$

where ω_0 is a reference expectation, ω_s and ω_l reflect the farmers' weighting on the recent and more distant past, and $W(\cdot)$ is a weighing function. The subscripts i and t denote the farm and year,

[2]A similar argument may hold for price expectations. However, prices are often revealed after harvest and farmers may fix prices early with commodity traders (Anastassiadis et al., 2014). If this is the case, there is less scope to respond to price changes than to weather changes in the course of the crop season.

respectively, and the recent and more distant past are separated by year T^* and defined over the horizon of T years. Thus, the effect of a weather event in past growing seasons on farmers' expectations for the current growing season depends on the magnitudes of ω_s and ω_l. Approximating weather expectations in this way is based on the assumption that farmers form adaptive expectations (Nerlove, 1958); that is, past experiences drive farmers' weather expectations (see also Cui & Xie, 2022; Li, 2023).[3] Furthermore, this approach allows the more recent and the more distant pasts to have different impacts on farmers' formation of weather expectations (Shafran, 2011; Wilke & Morton, 2017). Although T^* (that is, the cutting point between the more recent and the more distance pasts) must be chosen a priori, the weights placed on the more distant and on the more recent pasts are determined by the data without any prior assumptions.

3 | EMPIRICAL FRAMEWORK

3.1 | Structural equations

We approximate the farms' profit function in Equation (3) using a normalized quadratic functional form.[4] In line with the theoretical framework, the profit function includes expected and realized weather outcomes as profit shifters, and the weather variables are interacted with output and input prices (see also Sesmero et al., 2018), so that the marginal effects of individual crop prices on farm profits depend on weather outcomes. The functional form of the profit function with C crops, K variable inputs, M fixed inputs, and J weather variables is presented in the Data S1. With error terms (ε) added, the output supply and input demand functions are obtained by taking the first derivatives of this parameterized profit function with respect to the output and input prices (Hotelling, 1932):

$$q_c = \frac{\partial \tilde{\pi}}{\partial \tilde{p}_c} = \beta_c^p + \sum_{c'=1}^{C} \beta_{cc'}^{pp} \tilde{p}_{c'} + \sum_{k=2}^{K} \beta_{ck}^{pr} \tilde{r}_k + \sum_{m=1}^{M} \beta_{cm}^{pz} z_m + \sum_{j=1}^{J} \beta_{cj}^{pw} w_j + \sum_{j=1}^{J} \beta_{cj}^{pE[w]} E\left[w_j\right] + \varepsilon_{qc} \tag{6}$$

$$-x_k = \frac{\partial \tilde{\pi}}{\partial \tilde{r}_k} = \beta_k^r + \sum_{c=1}^{C} \beta_{ck}^{pr} \tilde{p}_c + \sum_{k'=2}^{K} \beta_{kk'}^{rr} \tilde{r}_{k'} + \sum_{m=1}^{M} \beta_{km}^{rz} z_m + \sum_{j=1}^{J} \beta_{kj}^{rw} w_j + \sum_{j=1}^{J} \beta_{kj}^{rE[w]} E\left[w_j\right] + \varepsilon_{xk} \tag{7}$$

To maintain readability, farm- and time-specific subscripts are not reported here. The tilde over a variable indicates that the variable has been normalized by the price of the first variable input, for example, $\tilde{\pi} = \pi / r_1$, which makes the profit function linearly homogeneous in prices. As the data cover a long period, which coincides with a trend toward warmer weather, we add linear and squared time trends to the regression equations to minimize the risk of a spurious relationship between weather variables and output supply or input demand.

Estimating the system of equations in Equations (6) and (7) identifies the effect of expected and realized weather on farmers' choices of output supply and input demand, and the parameters can be used to simulate farmers' responses in input and output choices in the event of a particular weather event.[5] In our main model, we estimate the structural Equations (6) and (7) in an unrestricted form to assess economic consistency. As a robustness check, we also estimate a restricted version in which the

[3]Previous studies have shown that farmers' experienced weather plays an important role in their production decisions (e.g., Alem et al., 2010; Ding et al., 2009).

[4]This functional form is locally flexible and allows for a straightforward imposition of price homogeneity. Contrary to the translog profit function, curvature can be maintained globally without sacrificing its flexibility.

[5]Equations (6) and (7) could be estimated jointly with the profit function. However, this approach often results in multicollinearity problems (Arnade & Kelch, 2007). Although (6) and (7) identify many but not all parameters from the original profit function, the identified parameters are sufficient for our purposes, as they allow evaluating price elasticities of supply and demand as well as the marginal effects of weather variables on profit-maximizing output and input levels.

theoretical property of convexity is imposed on the profit function using Cholesky factorization (Diewert & Wales, 1987; Lau, 1978). We also estimate a model with interaction terms between the weather variables and the fixed land input in the output supply and input demand functions to account for possible heterogeneity in behavioral responses to weather effects. Finally, we assess the robustness of the results with respect to the formation of weather expectations and functional form assumptions.

3.2 | Nonrandom crop selection

Farmers typically do not grow all of the crops considered in every year. The decision to grow a certain crop in a specific year depends on its relative expected profitability, which is, in turn, influenced by weather expectations, as well as economic, agronomic, and political factors. Thus, from an econometric perspective, farmers self-select into different cropping schemes. Estimating the output supply functions for the entire sample without considering this self-selection would result in biased parameter estimates, as we only observe farms' production levels for crops with a profitability above a certain (latent) threshold. The output supply functions in Equation (6) with censored dependent variables q_{cit} for farm i in year t can be written as (Lacroix & Thomas, 2011)

$$q_{\text{cit}} = d_{\text{cit}} \times q^{*}_{\text{cit}}, d_{\text{cit}} = I\left(d^{*}_{\text{cit}} > 0\right) \tag{8}$$

$$q^{*}_{\text{cit}} = \boldsymbol{X'}_{\text{cit}}\boldsymbol{\beta}_c + \alpha_{\text{ci}} + \nu_{\text{cit}} \tag{9}$$

$$d^{*}_{\text{cit}} = \boldsymbol{Z'}_{\text{cit}}\boldsymbol{\delta}_c + \eta_{\text{ci}} + u_{\text{cit}} \tag{10}$$

where q^{*}_{cit} and d^{*}_{cit} are the latent variables for the structural (i.e., output supply functions) and selection equations, respectively, and ν_{cit} and u_{cit} are the corresponding error terms. Vectors $\boldsymbol{X}_{\text{cit}}$ and $\boldsymbol{Z}_{\text{cit}}$ contain the explanatory variables for the structural and selection equations, respectively, and can share common elements. Vectors $\boldsymbol{\beta}_c$ and $\boldsymbol{\delta}_c$ contain the corresponding (unknown) parameters. I is an indicator function, such that d equals one if $d^{*}_{\text{cit}} > 0$. Finally, α_{ci} and η_{ci} are farm- and crop-specific fixed effects. To obtain consistent estimates of the output supply and input demand functions, we follow the two-step approach developed by Shonkwiler and Yen (1999).[6] In the first step, we estimate the probability that a farm grows a specific crop as a function of fixed inputs, lagged land shares, price and weather expectations, and a nonlinear time trend with probit regressions. By considering previous land-use choices in the crop selection equations, we account for agronomic constraints and the influence of crop rotations (Lacroix & Thomas, 2011).[7] Using the probability density function $\phi\left(\boldsymbol{Z'}_{\text{cit}}\widehat{\boldsymbol{\delta}}_c\right)$ and the cumulative distribution function $\Phi\left(\boldsymbol{Z'}_{\text{cit}}\widehat{\boldsymbol{\delta}}_c\right)$ of the estimated crop-specific selection equations, we then estimate the system of equations in the second step as

$$q_{\text{cit}} = \Phi\left(\boldsymbol{Z'}_{\text{cit}}\widehat{\boldsymbol{\delta}}_c\right) \times \boldsymbol{X'}_{\text{cit}}\boldsymbol{\beta}_c + \mu_c \phi\left(\boldsymbol{Z'}_{\text{cit}}\widehat{\boldsymbol{\delta}}_c\right) + \xi_{\text{cit}}, \tag{11}$$

[6]Studies using this approach in the agricultural economics literature include, among others, Sckokai and Moro (2006), Laukkanen and Nauges (2014), and Roosen et al. (2022). Lacroix and Thomas (2011) propose an extension of the approach to account for correlations between the choice of one crop and the error term of the supply function of another crop, but the required statistical properties (i.e., uncorrelated error terms between individual crop selection functions) were not satisfied in our empirical case.

[7]Hendricks, Smith, and Sumner (2014) show theoretically and empirically that the short-run response to price changes is larger than the long-run response, using the case of corn and soybean production in the US corn belt. This difference between long-run and short-run responses arises from the conversion of monocultures to crop rotations. It is unlikely that such dynamics affect our results on German crop farms, where monocultures are rarely observed.

where μ_c is another parameter to be estimated and ξ_{cit} is an error term with $E[\xi_{\text{cit}}] = 0$ (Shonkwiler & Yen, 1999).

To account for possible correlations between individual heterogeneity and the error terms of the crop selection and outcome equations, we use a fixed-effects estimation following Chamberlain (1984) and Mundlak (1978) by adding the farm-level averages of each independent variable to the vectors $\boldsymbol{X}_{\text{cit}}$ (i.e., in the structural equations) and $\boldsymbol{Z}_{\text{cit}}$ (i.e., in the selection equations). After linearizing Equation (11), the system of output supply and input demand functions can be estimated using seemingly unrelated regressions (Zellner, 1962). As discussed above, we also estimate a restricted version of the profit system to impose convexity. Owing to the nonlinearity of the parameters for the Cholesky factorization, the restricted profit system is estimated using feasible generalized nonlinear least squares. Finally, to consider the uncertainty in the parameters obtained from the first-stage probit regressions, standard errors and confidence intervals are obtained using nonparametric bootstrapping with 1000 replications.

Because weather and price expectations are included in both the selection (whether to grow a specific crop) and structural (how much to produce from a certain crop) equations, the marginal effects in both stages must be accounted for when estimating production responses (Su & Yen, 2000). For example, the semi-elasticity of crop c with respect to the expected weather outcome $E[w_j]$ is calculated as

$$\begin{aligned}
\varepsilon_{q_{\text{cit}},E[w_j]} &= \frac{\partial E\left(q_{\text{cit}}|\boldsymbol{X}'_{\text{cit}},\boldsymbol{Z}'_{\text{cit}}\right)}{\partial E\left[w_{\text{jit}}\right]} \times \frac{100}{q_{\text{cit}}} \\
&= \left(\Phi\left(\boldsymbol{Z}'_{\text{cit}}\widehat{\boldsymbol{\delta}}_c\right) \times \frac{\partial\left(\boldsymbol{X}'_{\text{cit}}\widehat{\boldsymbol{\beta}}_c\right)}{\partial E\left[w_{\text{jit}}\right]} + \frac{\partial\Phi\left(\boldsymbol{Z}'_{\text{cit}}\widehat{\boldsymbol{\delta}}_c\right)}{\partial E\left[w_{\text{jit}}\right]} \times f\left(\boldsymbol{X}_{\text{cit}},\widehat{\boldsymbol{\beta}}_c\right) + \widehat{\mu}_c \times \frac{\partial\phi\left(\boldsymbol{Z}'_{\text{cit}}\widehat{\boldsymbol{\delta}}_c\right)}{\partial E\left[w_{\text{jit}}\right]}\right) \times \frac{100}{q_{\text{cit}}} \\
&= \left(\Phi\left(\boldsymbol{Z}'_{\text{cit}}\widehat{\boldsymbol{\delta}}_c\right) \times \widehat{\beta}_{cj}^{pE[w]} + \phi\left(\boldsymbol{Z}'_{\text{cit}}\widehat{\boldsymbol{\delta}}_c\right) \times \boldsymbol{X}'_{\text{cit}}\widehat{\boldsymbol{\beta}}_c \times \widehat{\delta}_{cj}^{E[w]} - \widehat{\mu}_c \times \left(\boldsymbol{Z}'_{\text{cit}}\widehat{\boldsymbol{\delta}}_c\right) \times \widehat{\delta}_{cj}^{E[w]} \times \phi\left(\boldsymbol{Z}'_{\text{cit}}\widehat{\boldsymbol{\delta}}_c\right)\right) \\
&\quad \times \frac{100}{q_{\text{cit}}}
\end{aligned} \tag{12}$$

The semi-elasticity in (12) quantifies the percentage change in q_{cit} in response to a one-unit change in $E[w_{jit}]$, considering changes in both the crop selection probability and the optimal production level of q_{cit}.

3.3 | Simulation of production responses to an extreme weather event

It is not straightforward to interpret the (semi-) elasticities of various weather variables in isolation. For example, the ceteris paribus interpretation of the effect of the number of dry days requires holding total precipitation fixed, which can be an unreasonable condition in practice. In such a situation, simulation exercises can help better understand the effects of specific weather outcomes on production choices. In addition, transformative events, such as droughts, may impact farmers' behavior differently from incremental events, such as gradual changes in temperature (Wilke & Morton, 2017). Hence, we assess the immediate and lasting effects of a particular weather event by simulating farm-level responses to a one-year drought shock over a period of 10 years, motivated by Ramsey et al. (2021),[8] based on the estimated parameters from the selection equations and the output supply and input demand functions.

As an exemplary case, we use the 2018 European drought for the simulation, which led to severe crop losses in Germany and other European countries (Webber et al., 2020). We consider a

[8]Ramsey et al. (2021) use crop choice data at the individual plot level but without information on farm-level decisions on input and output quantities.

2018-like drought shock occurring in period $t = 0$. At $t = -1$, we set all weather variables to their sample averages, which we define as the long-term average weather.[9] This period serves as the baseline for subsequent years. At $t = 0$, the realized weather variables are set to the German average values for the drought year 2018, whereas the lagged variables are still equal to their long-term averages. In subsequent years, the experienced drought shock influences the lagged variables from the more recent and more distant pasts. The detailed formula for computing these variables and their values are presented in the Data S2.

The simulated levels of output supply and input demand are obtained in two steps. First, we plug the simulated values of the weather variables for each year from $t = -1$ to $t = 10$ into the estimated selection equations to compute the simulated values for the probability density and cumulative distribution functions for each farm observation. Second, the simulated weather values are plugged into the structural equations, along with the values for the probability density and cumulative distribution functions from $t = -1$ to $t = 10$. In both the selection and structural equations, all other variables, such as prices, are held fixed to isolate the production responses to the weather shock.

4 | DATA

4.1 | Farm production data

We employ accountancy data from German crop farms for the period 1996–2019.[10] The sample is from the German Farm Accountancy Data Network (FADN) provided by the German Federal Ministry of Food and Agriculture (BMEL) and constitutes Germany's contribution to the European FADN, which is widely used in the literature (e.g., Ang, 2019; Baldoni & Esposti, 2020; Moore & Lobell, 2014). This dataset is a rotating unbalanced panel stratified according to region, type of specialization, and economic size to ensure its representativeness of commercial agricultural holdings. Farmer participation is voluntary but encouraged by federal state committees following selection plans based on the Farm Structure Survey results. Farmers benefit from participation through monetary compensation and more effective farm consultation service. We do not expect systematic differences between farmers who enter, remain, or exit the farm survey (i.e., no attrition bias) but emphasize that the sample is representative of commercial and forward-looking farms, and not the full farm population.

To be able to account for unobserved farm heterogeneity, we retain farms that have remained in the sample for at least three consecutive years (1 year will be dropped from the estimation because of the inclusion of lagged variables). The resulting sample consists of 14,796 observations from 1638 farms. On average, 8.5% (7.1%) of farms enter (exit) the panel per year, and the average sample period of a farm is 9.0 years. For the empirical analysis, we merge the produced crops into five categories: cereals except corn (mainly wheat, barley, and rye); protein crops (beans and peas); oilseeds (mainly canola); root crops (sugar beets and potatoes); and corn (both for grain and silage production). The crops are categorized such that individual crop categories have similar agronomic characteristics, such as water and nutrient demands, or soil requirements. Cereals and oilseeds are primarily used as winter crops in Germany (i.e., planted in the fall and harvested in the summer and fall of the following year), whereas protein crops, root crops, and corn are spring crops (i.e., planted in the spring and harvested in the summer and fall of the same year).

Table 1 presents the means and standard deviations of the main variables used in the analysis averaged over the entire sample period (1996–2019), along with the within- and between-farm

[9]We also used the long-term averages from 1965 to 1995 as benchmark values, but this resulted in unrealistic values due to out-of-sample prediction, as growing degree days and other weather variables have considerably changed between the period 1965 to 1995 and our sample period 1996 to 2019.

[10]The year 1995 is also covered in the data but dropped from the analysis due to the inclusion of lagged values for land shares and crop prices in the regression equations.

standard deviations.[11] Additional descriptive statistics for individual years are presented in the Data S3. Averaged over all years, cereals are grown on 99% of all farms in our sample of specialized crop farms, followed by root crops (71%), and oilseeds (59%). Corn (25%) and protein crops (16%) are grown on a smaller number of farms, underscoring the need to address nonrandom crop selection in econometric estimations.

The expected prices for each crop category are computed as lagged regional (NUTS 2)-level weighted averages by dividing the sum of the crop revenues in a specific region by the region's total quantity. We use lagged prices as a proxy for expected prices because farmers have no other information about prices to be achieved at the end of the crop year when making their production decisions at the beginning of the crop year. Although several approaches exist for modeling price expectations (see Wu et al., 2004 for an overview), Chavas et al. (1983) showed that using lagged market prices or futures prices makes little difference because they reflect similar market information. Future markets in Germany are only available for canola, corn, and wheat, and they are rarely used by the farmers (Adämmer et al., 2014; Michels et al., 2019). We choose regional average prices over farm-level prices for two reasons. First, farm-level prices include quality premiums and discounts, and therefore mask quality differences in the production quantity (e.g., Dalhaus et al., 2020; Reinhard et al., 1999). Second, in our dataset, farm-level prices are reported only for farms producing a specific crop, whereas the crop choice also depends on the price of alternative crops. Regional prices, by contrast, implicitly consider quality differences and are available for every farm. As reported by the descriptive statistics in Table 1, oilseeds achieve the highest price per decision on average in our sample, followed by protein crops, cereals, root crops, and corn.

We consider two variable inputs (fertilizer and other material inputs) and three fixed inputs (land, labor, and capital). The price of fertilizer is measured at the country level based on country-level application rates and the unit prices of nitrogen, phosphate, potash, and calcium oxide, obtained from BMEL (2021). We divide farm-level fertilizer expenses by the country-level fertilizer price to measure fertilizer quantities at the farm level. For other material inputs (e.g., seed, pesticides, material, energy, contract services, and water use), we calculate implicit quantities by dividing total expenses by a Tornquist price index[12] (e.g., Henry de Frahan et al., 2011; Koutchadé et al., 2021) constructed at the regional (NUTS 2) level. Following Lacroix and Thomas (2011), we chose other material inputs as the numeraire in our estimation procedure, because no physical quantity for this input can be obtained from the accountancy data set. As a result, the input demand function is estimated for fertilizer quantities but not for other material inputs. For fixed inputs, we consider land (measured in hectares), labor (annual working units), and capital use (deflated depreciation).

4.2 | Weather data

Weather data were officially provided by the Deutscher Wettedienst (DWD, *engl.* German Meteorological Service) at 1 × 1 km grid cells for the period 1960–2019 (DWD, 2021). To match weather records with farm-level data, we aggregated them at the municipality (LAU 2, formerly NUTS 5) level.[13] With more than 11,000 municipalities in Germany, the average size of each municipality is approximately 33 km^2, allowing for a good approximation of weather outcomes at the farm level. Following Ramsey et al. (2021), we consider the following weather variables: growing degree days between 10 and 30°C (GDD), growing degree days above 30°C (HighGDD), sum of precipitation in mm (PREC), and the number of dry

[11]Between-standard deviation is calculated as $SD_b = \sqrt{\frac{\sum_{i=1}^{n}\left(\overline{y}_{i.} - \overline{\overline{y}}_{..}\right)^2}{n-1}}$ and within-standard deviation is calculated as $SD_w = \sqrt{\frac{\sum_{i=1}^{n}\sum_{t=1}^{T}\left(y_{it} - \overline{y}_{i.}\right)^2}{n(T-1)}}$, where $\overline{\overline{y}}_{..}$ is the arithmetic mean of all observations, $\overline{y}_{i.}$ is the arithmetic mean of one individual farm, and n is the total number of farms.

[12]The Tornquist price index for input k in NUTS 2 region n in year t is given by $r_{knt} = \prod_{k' \in k} \left(\frac{r_{k't}}{r_{k's}}\right)^{\frac{g_{k'nt} + g_{k'ns}}{2}}$ with $g_{k'nt} = \frac{\sum_{i \in n} V_{k'it}}{\sum_{k'' \in k} \sum_{i \in n} V_{k''it}}$, where -$s$ is the basis year, $r_{k't}$ is the country-level price index of item k' belonging to input category k in year t, and $V_{k'it}$ is the expenditure on input item k' of farm i in year t.

[13]We used the municipalities of the year 2007 because of border adjustments during the period of the study.

TABLE 1 Descriptive statistics for variables used in the analysis, 1996–2019.

Statistic	Mean (all years) (1)	St. dev. (all years) (2)	Within-st. dev. (3)	Between-st. dev. (4)
Cereals quantity (dt)	8405.772	14983.158	1862.405	14267.201
Protein crops quantity (dt)	147.344	672.089	209.905	595.109
Oilseeds quantity (dt)	1091.398	2422.868	601.108	2109.782
Root crops quantity (dt)	10108.685	17292.825	3228.567	16267.449
Corn quantity (dt)	1746.158	8946.501	3721.890	7334.818
Fertilizer quantity (kg pure nutrients)	72.065	130.568	32.442	115.511
Other material input (const. EUR)	1020.085	1434.456	197.834	1375.054
Cereals price (EUR/dt)	12.383	3.475	1.655	2.539
Protein crops price (EUR/dt)	14.502	6.828	3.060	5.221
Oilseeds price (EUR/dt)	28.131	8.975	4.301	7.222
Root crops price (EUR/dt)	6.669	2.741	0.880	2.560
Corn price (EUR/dt)	6.032	38.334	22.707	13.265
Fertilizer price (EUR/t)	382.098	86.537	44.996	60.047
Other materials price (index)	84.938	15.333	6.982	13.432
Cereals quantity >0 (yes or no)	0.987	0.112	0.040	0.113
Protein crops quantity >0 (yes or no)	0.161	0.367	0.150	0.294
Oilseeds quantity >0 (yes or no)	0.585	0.493	0.163	0.439
Root crops quantity >0 (yes or no)	0.712	0.453	0.112	0.442
Corn quantity >0 (yes or no)	0.254	0.435	0.170	0.375
Share cereals area (%)	0.665	0.169	0.061	0.161
Share protein crops area (%)	0.015	0.046	0.019	0.036
Share oilseeds area (%)	0.118	0.128	0.048	0.108
Share root crops area (%)	0.147	0.170	0.031	0.180
Share corn area (%)	0.054	0.134	0.042	0.134
Total area (ha)	205.304	311.999	23.155	303.311
Labor (annual working unit)	2.298	4.205	0.544	3.953
Depreciation (EUR)	419.020	673.203	137.960	617.650
Number of growing degree days (10–30°C), Mar-Aug (*GDD*)	953.762	126.674	51.916	108.064
Precipitation (mm), Mar-Aug (*PREC*)	314.266	79.430	38.733	52.587
Number of growing degree days >30°C, Mar-Aug (*GddHigh*)	3.527	4.171	2.232	2.636
Number of dry days (precipitation <1 mm), Mar-Aug (*DD*)	118.992	11.348	5.891	7.368
*GDD*1to3	940.385	99.542	22.786	97.226
*PREC*1to3	314.132	58.541	18.938	54.372
*GddHigh*1to3	3.241	2.587	1.055	2.184
*DD*1to3	119.435	8.368	3.521	7.204
*GDD*4to10	923.448	95.678	14.949	95.010
*PREC*4to10	305.999	50.674	9.531	49.027
*GddHigh*4to10	2.728	1.751	0.515	1.624
*DD*4to10	120.410	6.531	1.654	5.963

Note: Number of observations: 14,796. *GDD*1to3 indicates growing degree days averaged over years $t - 1$ to $t - 3$, *GDD*4to10 over years $t - 4$ to $t - 10$, and so on.

days with less than 1 mm precipitation (DD).[14] Growing degree days are calculated by fitting a sine curve over the daily minimum and maximum temperatures, as suggested by D'Agostino and Schlenker (2016), who followed Snyder (1985) and Schlenker and Roberts (2009). All weather variables are measured during the growing season (March–August). The four weather variables are selected to describe the average climatic conditions (growing degree days and precipitation) as well as extreme weather conditions (growing degree days above 30°C and the number of dry days).

Table 1 shows that, averaged over all farms and years, the growing degree days from March to August amount to 953.8 days, and the average sum of precipitation is 314.3 mm. Furthermore, farms in the sample observe, on average, 119.0 dry days and 3.5 growing degree days above 30°C. As described above, we include the averages of more recent and more distant weather observations to approximate farmers' weather expectations. Specifically, we add a lag structure that measures each variable based on years $t-1$ to $t-3$, denoted by GDD1to3 for growing degree days, and based on years $t-4$ to $t-10$, denoted by GDD4to10, for instance. As expected, the main variation in the weather variables (as well as in the production variables) arises from between-farm variability. Nevertheless, there is also substantial within-farm variation in most variables, as shown in Column (3). As our estimation approach uses a fixed-effects procedure, a lack of within-farm variability would result in inflated standard errors but would not bias the results. The cross-sectional and temporal variations in growing degree days are visualized in Figure 1 for three selected years, and the corresponding figures for all other weather variables are reported in the Data S3.

5 | RESULTS AND DISCUSSION

We first present the results from the first-stage probit models given their economic meaning, before discussing price and weather elasticities, and finally, the results from the simulation exercise.[15] All estimations were performed using the statistical software *R* (R Core Team, 2020). The seemingly unrelated regressions were estimated using the *systemfit* package (Henningsen & Hamann, 2007) and feasible generalized nonlinear least squares were estimated using the *nlsur* package (Garbuszus, 2021). We obtained 95% confidence intervals by taking the empirical quantiles of the bootstrapped distribution of parameter estimates and resampled entire clusters to obtain cluster-robust confidence intervals (Cameron et al., 2008). For the main results, we clustered at the farm level, because we expect unexplained variation in the dependent variables that is correlated across time, whereas unobserved time-invariant spatial variation across farms is accounted for by the fixed effects. We also tested the sensitivity of the confidence intervals to clustering at the regional (NUTS 2) level. Although the confidence intervals increase slightly with the level of clustering, the levels of significance remain unaffected in most cases. For example, 28 of the 31 weather semi-elasticities that are statistically significant at the 95% level when clustering at the farm level are statistically significant at the same level when clustering at the regional level (see Data S4).

5.1 | First-stage regression results: Crop choice

The results of the first-stage regressions show how the expected weather outcomes, prices, and fixed inputs affect the crop choice. The full parameter estimates from the probit regressions are reported

[14]As noted by Ramsey et al. (2021), the thresholds for growing degree days are likely to vary across crops and across climatic regions. For example, Schmitt et al. (2022) found that heat thresholds for wheat, barley, canola, and maize in Germany vary between 29 and 34°C during the flowering phase. Our choice is a conservative one that aims to capture production responses across all crops.

[15]We validated the model by excluding the final year of the data (year 2019) and compared the predicted values for this year with the observed values. As reported in Data S7, the root mean squared errors and mean absolute errors are only slightly larger for the year 2019 than for the years that were included in the estimation. In addition, the correlation between observed and predicted values in 2019 varies between 0.575 for oilseeds and 0.944 for cereals, indicating a reasonable predictive power of the model.

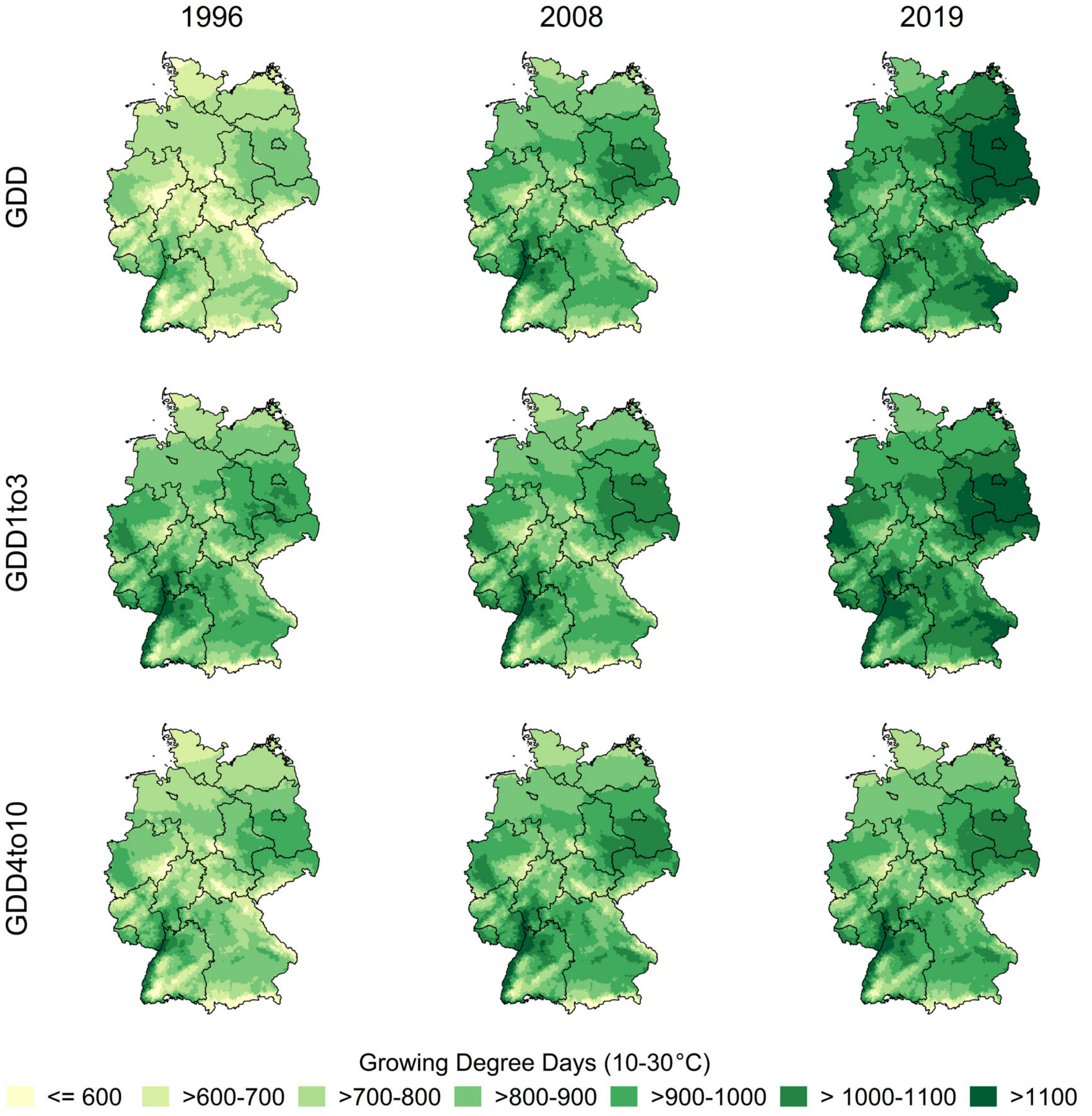

FIGURE 1 Temporal and cross-sectional variation in growing degree days (GDD).

in Table A1 in the appendix along with their 95% confidence intervals. Economic theory implies that the probability of growing a specific crop is nondecreasing in its own price. Consistent with expectations, the estimated coefficients of own prices are positive for all five crop categories and statistically significant at the 5% level for oilseeds and root crops. The lagged shares of crop areas are strong predictors of current crop decisions. Of the 40 estimated coefficients of the lagged weather variables, 12 are statistically significant at least at the 5% level. As there are both linear and quadratic terms for these variables, and the coefficients of the probit model do not represent marginal effects, we quantify the effect of weather expectations on the probability of growing a certain crop by computing the average partial effects.

For interpretation, we add the partial effects of the more recent and more distant pasts to assess the net effect of weather expectations (Ramsey et al., 2021). The resulting average partial effects are shown in Figure 2. Evaluated at the sample mean, the farm-level decision to grow cereals does not respond to changes in any of the four weather variables. This result is expected, because nearly all farm observations in our sample engage in cereals production. Similarly, the decision to grow root crops is not sensitive to changes in weather expectations. This result can be explained by the specific machinery requirements for potatoes and sugar beets, as well as the existence of nontradable delivery rights for sugar beets (see, e.g., Wimmer & Sauer, 2020).[16] For the selection of the remaining crops, statistically significant weather effects are found. Higher expected precipitation but also a higher expected number of dry days increase the probability to plant protein crops. For example, at the sample mean, expecting 1 cm more precipitation increases the probability to plant protein crops by 1.3 percentage points, ceteris paribus. Oilseeds choice is negatively affected by expected growing degree days, precipitation, and dry days, and positively affected by the expected number of degree days above 30°C. Corn is less likely to be planted under an increased expected number of dry days.

5.2 | Second-stage regression results: Price and weather elasticities

The model fit and full parameter estimates of the system of output supply and input demand functions are presented in Tables A.2 and A.3 in the Appendix A. As indicated by the R^2 values, the explanatory variables explain between 31% (corn supply) and 91% (cereals supply) of the variation in the observed output and input quantities, indicating a reasonable fit of the econometric model. Coefficients of the selection terms included in the structural equations are all statistically significant at the 1% level, except for cereals, implying that controlling for nonrandom crop selection is necessary.[17] The parameter estimates also confirm that both realized weather and weather in the recent as well as in the more distant past affect the profit-maximizing output supply and input demand, as indicated by statistically significant coefficients of observed and lagged weather variables. In several cases, responses to recent and distant weather changes revert in sign (e.g., *Prec1to3* and *Prec4to10* in the cereals supply function). This result can be attributed to the expectation-formation process of the farmers. The mentioned example suggests that changes in precipitation in the recent past lead to different expectations of precipitation for the current year, compared with the same change in precipitation in the more distant past.

To assess the economic consistency of our model, we report the estimated own-price elasticities of crop supply and variable input demand in Table 2, which are again evaluated at the sample mean. Economic theory dictates that profit-maximizing output quantities are nondecreasing in own prices and profit-maximizing input quantities are nonincreasing in own prices. This is the case for all the considered outputs and inputs.[18] For example, evaluated at the sample mean, cereals supply increases by 0.43% if cereals prices increase by 1%, and fertilizer demand declines by 0.12% in response to a 1% increase in fertilizer price.

The estimated own-price elasticities of protein crops and corn supply are not statistically significant and are smaller in magnitudes than the remaining crops, indicating that the output levels of these crops are not highly influenced by their prices in the short run. Protein crops may be primarily grown for environmental and agronomic reasons, and corn is often grown for biogas production and animal feed (although our sample does not include farms with livestock production). Thus, the energy price may be a more important determinant of corn supply for these farms. Contrary to own-price elasticities, cross-price elasticities can take either sign because there may be synergies between crops or crop-rotational requirements. In this case, the optimal supply of one crop increases

[16]We note that the results represent the partial effects evaluated at the sample mean. There may be more pronounced changes in the crop portfolio with a larger shift of the climate, but this is beyond the scope of our data and analysis.

[17]Data S8 presents results from a model that ignores the nonrandom crop selection. Results from the simulation of the weather shock are qualitatively similar, except for the medium-term response in root crops production. Both price and weather elasticities differ in magnitudes and, in some cases, in signs from the original model.

[18]This result applies to all observations as the second-order derivatives of the quadratic profit function are constants.

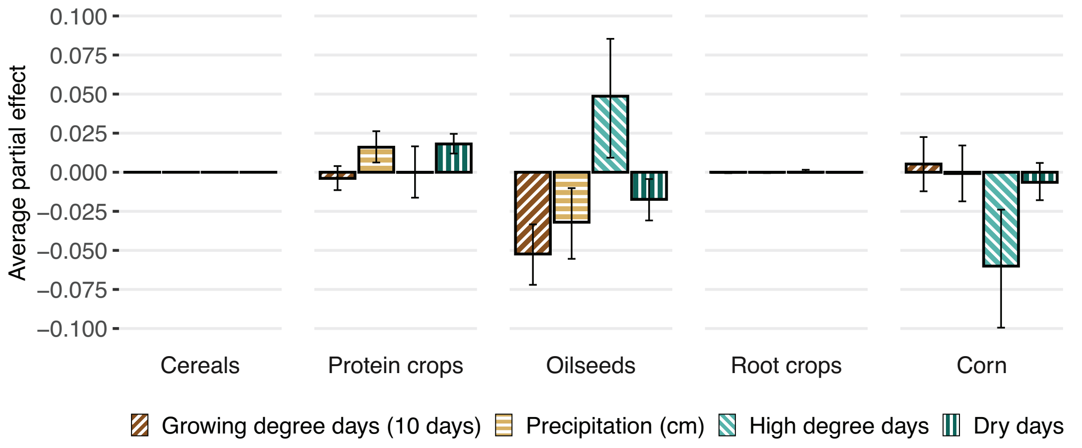

FIGURE 2 Average partial effects of weather expectations on crop choice. Vertical bars indicate 95% confidence intervals obtained from nonparametric bootstrapping ($n = 1000$).

with an enhanced supply of the other crop. For example, increasing cereals prices not only enhances cereals production, but also oilseeds and corn production, at the expense of protein crops.

Next, we evaluate how the optimal output supply and input demand respond to changes in the expected and realized weather outcomes. Analogous to the interpretation of the crop-selection equation, we calculate the net effect of expected weather by adding the marginal effects of weather outcomes in the more recent and more distant pasts. Table 3 shows the semi-elasticities of the crop supply and input demand with respect to the four weather variables considered. We recall that these elasticities do not represent pure weather-yield effects. Instead, they indicate how profit-maximizing supply and demand change under different weather expectations and realizations. If the yield of a particular crop is not affected by a certain weather change but the yields of other crops planted on the same farm are negatively affected, it can be economically rational for the farmer to allocate more resources (e.g., labor or fertilizer) to the crop that is not affected, as the relative profitability of this crop has increased. Thus, we would observe a positive effect on the supply of this particular crop, without any direct weather effect on the yield.

According to the estimation results, a higher number of growing degree days between 10 and 30°C during the current growing season decreases the supply of cereals, protein crops, and oilseeds but increases the supply of root crops. For example, ceteris paribus, an increase in the number of growing degree days by 1 day results in 0.07% less cereals supply. Higher realized precipitation reduces the supply of cereals and oilseeds; more growing degree days above 30°C increase cereals, protein crops, and oilseeds supply but decrease root crops and corn supply; and more dry days in the current year are detrimental for cereals, protein crops, and oilseeds. All other weather variables being equal, fertilizer demand is reduced under a larger number of growing degree days and increased under more precipitation, more growing degree days above 30°C, and more dry days. With respect to past weather, based on which weather expectations are formed, Table 3 shows that statistically significant results carry the same sign in most cases, except for dry days with respect to protein supply and growing degree days above 30°C with respect to fertilizer supply. A likely explanation is that changes in the expected weather affect the relative profitability of crops, which leads farmers to reallocate resources across crops.

As previously discussed, these weather effects must be interpreted with care, because the ceteris paribus interpretation is not always sensible. For example, if a heavy precipitation event occurs in a particular year and the total amount of total precipitation is held constant, the number of dry days must increase, even though the year was overall not drier than usual. Furthermore, drought years are

TABLE 2 Own- and cross-price elasticities.

	Q cereals	Q protein cr. (2)	Q oilseeds (3)	Q root crops (4)	Q corn (5)	X fertilizer (6)	X others (7)
P cereals	0.427***	−0.363***	0.527***	0.002	0.610***	0.795***	0.450***
	(0.365; 0.484)	(−0.649; −0.173)	(0.321; 0.752)	(−0.078; 0.035)	(0.300; 0.881)	(0.693; 0.910)	(0.343; 0.560)
P protein cr.	0.014	0.069	0.287***	0.067**	0.039	0.047*	−0.006
	(−0.018; 0.042)	(−0.070; 0.219)	(0.157; 0.409)	(0.013; 0.123)	(−0.072; 0.154)	(−0.001; 0.095)	(−0.020; 0.005)
P oilseeds	0.140***	0.071	1.509***	−0.015	−0.144	−0.703***	1.062***
	(0.094; 0.193)	(−0.236; 0.293)	(1.182; 1.816)	(−0.061; 0.043)	(−0.476; 0.193)	(−0.814; −0.576)	(0.871; 1.252)
P root cr.	0.008	0.132	−0.112	0.134**	−0.233**	−0.024	0.156**
	(−0.014; 0.028)	(−0.054; 0.326)	(−0.266; 0.031)	(0.017; 0.258)	(−0.446; −0.021)	(−0.083; 0.037)	(0.021; 0.275)
P corn	5e−05	−0.006	−0.003*	0.001	0.003	−4e−04**	0.131***
	(−1e−04; 2e−04)	(−0.012; 0.045)	(−0.035; 5e−04)	(−0.001; 0.002)	(−0.009; 0.010)	(−0.001; −6e−05)	(0.027; 0.218)
R fertilizer	−0.212***	−0.143	0.856***	0.007	0.728***	−0.115	−1e−04
	(−0.244; −0.186)	(−0.374; 0.069)	(0.593; 1.137)	(−0.044; 0.030)	(0.259; 1.131)	(−0.267; 0.048)	(−0.085; 0.089)
R others	−0.377***	0.242	−3.063***	−0.196**	−1.002***	3e−04	−1.793***
	(−0.468; −0.287)	(−0.202; 0.809)	(−3.567; −2.584)	(−0.345; −0.027)	(−1.612; −0.215)	(−0.284; 0.264)	(−2.059; −1.489)

Note: Elasticities are evaluated at the sample means. 95% confidence intervals, presented in parentheses, are obtained using nonparametric bootstrapping with $n = 1000$.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 3 Weather semi-elasticities of output supply and input demand.

	Q cereals (1)	Q protein cr. (2)	Q oilseeds	Q root crops (4)	Q corn (5)	X fertilizer (6)
Observed weather						
GDD (days)	-0.069^{***}	-0.067^{***}	-0.077^{***}	0.045^{**}	-0.159	-0.123^{***}
	(−0.082; −0.058)	(−0.106; −0.022)	(−0.113; −0.041)	(0.008; 0.076)	(−0.413; 0.062)	(−0.148; −0.100)
PREC (mm)	-0.036^{***}	-0.026	-0.116^{***}	-0.008	-0.043	0.063^{***}
	(−0.052; −0.021)	(−0.094; 0.035)	(−0.172; −0.059)	(−0.044; 0.029)	(−0.366; 0.218)	(0.037; 0.088)
GDD high (days)	0.482^{***}	1.527^{**}	1.115^{***}	-3.531^{***}	-2.137^{**}	1.535^{***}
	(0.272; 0.702)	(0.333; 2.418)	(0.466; 1.930)	(−4.088; −2.908)	(−3.957; −0.207)	(1.102; 2.036)
Dry days (days)	-0.400^{***}	-0.620^{**}	-0.787^{***}	0.166	-0.367	1.143^{***}
	(−0.495; −0.313)	(−1.143; −0.042)	(−1.134; −0.438)	(−0.126; 0.460)	(−1.471; 0.668)	(0.918; 1.375)
Past weather						
GDD (days)	-0.262^{***}	-0.644^{***}	-1.858^{***}	1.146^{***}	-0.182	-0.156
	(−0.346; −0.175)	(−1.026; −0.172)	(−2.325; −1.322)	(0.739; 1.458)	(−2.128; 1.374)	(−0.357; 0.042)
PREC (mm)	0.068	1.135^{***}	-1.581^{***}	0.714^{***}	-1.128	0.002
	(−0.041; 0.167)	(0.515; 1.726)	(−2.199; −1.029)	(0.326; 1.134)	(−3.150; 1.239)	(−0.223; 0.230)
GDD high (days)	1.550	5.378	14.400^{**}	-27.957^{***}	-40.343^{***}	-6.782^{***}
	(−0.374; 3.268)	(−5.643; 16.124)	(4.356; 24.832)	(−36.901; −17.498)	(−65.418; −17.286)	(−11.197; −2.211)
Dry days (days)	0.154	7.017^{***}	-7.015^{***}	0.977	-11.564	1.097
	(−0.475; 0.787)	(3.335; 11.640)	(−10.316; −3.428)	(−0.934; 2.903)	(−26.738; 5.124)	(−0.733; 2.872)

Note: Semi-elasticities are evaluated at the sample means. 95% confidence intervals, presented in parentheses, are obtained using non-parametric bootstrapping with $n = 1000$.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

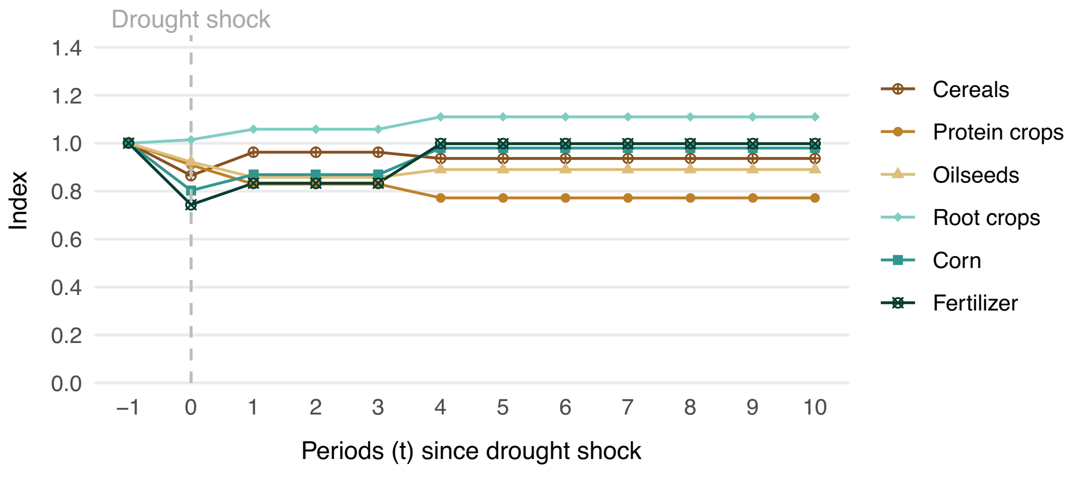

FIGURE 3 Simulated changes in crop supply and fertilizer demand after a drought occurring in $t = 0$.

often characterized not only by little precipitation but also by a comparatively higher number of growing degree days. Therefore, it is challenging to disentangle the individual supply effects of both variables. To obtain a better understanding of how different weather outcomes, both in the past and in the current year, affect farmers' production decisions, we simulate the production outcomes of a weather shock in the following section.

5.3 | Simulation results

We simulate the response to a weather shock over 10 years to cover the entire time span of the weather variables. To simulate the effect of a drought event on the output supply and input demand, we set the weather variables to hypothetical values as explained in Section 3.3. All other observed variables (e.g., prices and fixed inputs) are held fixed in this simulation exercise.[19] When interpreting these results, it must be noted that fixed inputs (land, labor, and capital) may be adjusted in the course of weather trends (see, e.g., Yang & Richard Shumway, 2016) or shocks. To determine whether the level of fixed inputs affects farm-level responses to weather shocks, we investigate heterogeneous responses across farm sizes below.

Figure 3 shows the change in output supply for the different crops and input demand for the fertilizer input in the year of the drought shock ($t = 0$), as well as 10 years after the shock ($t = 1, 2, \dots 10$), with $t = -1$ (i.e., the long-term average) as the base year. In the drought year, supply of all crops, except for root crops, and fertilizer demand decline. Of all the considered crop categories, corn supply suffers the most from the shock (−20% below average levels), in line with the crop's comparatively high water demand. Although root crops are also characterized by high water demand, they are often grown under irrigation, which can explain why they barely respond to the drought shock. However, we cannot test this hypothesis in this empirical study because the data do not include crop-specific information on irrigation.[20]

[19]We focus on changes in weather variables while holding prices fixed, as price–yield correlations are very low at the individual farm level (Finger, 2012).

[20]Overall, less than 5% of agricultural land in Germany is equipped for irrigation (Schmitt et al., 2022; Siebert et al. 2015). The lack of crop-specific irrigation use in our data implies that that we cannot account for the fact that irrigated crops respond differently to weather shocks than rainfed crops (e.g., Wang et al., 2021) in the supply and demand functions. Hence, our results reflect the average response of farms to weather changes, given the current state of irrigation and other management practices. It is well possible that future irrigation investments will increase the resilience of crop production to drought shocks.

Furthermore, the simulation reveals that a drought shock has long-lasting effects on output supply. Corn production remains at reduced levels in the few years after the shock, whereas the output levels of oilseed crops and, in particular, protein crops remain at reduced levels in the longer term. By contrast, cereals production is only marginally affected by the drought and returns to nearly original levels immediately in the following year, and root crops supply tends to increase over time. Moreover, although oilseeds and protein crops supplies respond only slightly in the year of the drought (close to 10%), their decline is more pronounced in subsequent years (−14% and −17%, respectively). As discussed above, protein crops are primarily grown for environmental and agronomic reasons in Germany and do not constitute a major source of income. After a drought year, farmers may reduce their protein crops production to financially compensate for the losses caused by the drought.

Finally, Figure 3 shows that farmers respond to the lower growth potential of crops during and in the direct aftermath of an extreme weather year by reducing fertilizer demand. This effect lasts for several years before returning to the baseline level. The fact that input use depends on weather conditions in the current year has also been reported by Möhring et al. (2022) and Alem et al. (2010). These simulation results demonstrate the importance of considering the dynamic nature of farmers' responses to extreme weather, with respect to both crop-specific output supply and input demand.

5.4 | Heterogeneous responses to weather trends

Previous studies have shown that farm size plays an important role in adaptation capacity, although its impact varies across countries (Reidsma et al., 2009). Considering the observed structural change in agriculture toward fewer but larger farms (e.g., Neuenfeldt et al., 2019), we here explore heterogeneous responses to weather trends across different farm sizes, approximated by the area of farmed land. To allow for heterogeneous responses in our model, we add interaction terms between weather variables and the land variable in the structural and selection equations. Hence, the weather elasticities of output supply and input demand as well as the simulated response to the drought shock vary across farm sizes. The full parameter estimates for the extended model, estimated price elasticities, and estimated weather semi-elasticities are presented in Data S5. In both the selection and structural regression results, several interaction terms between the weather variables and agricultural land are statistically significant, indicating heterogeneous responses to weather trends across farms of different sizes. Figure 4 shows the simulation results at the sample mean as well as averaged over farms endowed with fewer and more hectares of land than the median number of hectares. In our empirical case of German crop farms, smaller farms are more affected by the weather shocks than larger farms. This finding is in line with Spiegel et al. (2021) who found that smaller farms are more concerned about short-term shocks. A possible explanation for our results is that large farms may have greater personal and technological capacities to absorb shocks. Based on this result, we can infer that adjustments in fixed inputs and the trend toward larger farms may increase the resilience of the farm sector to weather shocks; however, further research is needed to explore the underlying mechanisms.

5.5 | Robustness

We estimated a range of additional models to test the robustness of our results to alternative specifications for the weather variables. First, we tested the sensitivity of the results to changes in the time periods that define the more recent and more distant past. The estimation results, price and weather elasticities and simulation results for alternative periods ($t-1$ to $t-5$ and $t-6$ to $t-10$; $t-1$ to $t-5$ and $t-6$ to $t-20$; $t-1$ and $t-2$ to $t-10$) are presented in the Data (S6.1–6.3). The price and weather elasticities at the sample mean are similar to the main specification, both in magnitude and in statistical significance. Although the speed of adjustments varies with the choice of lag

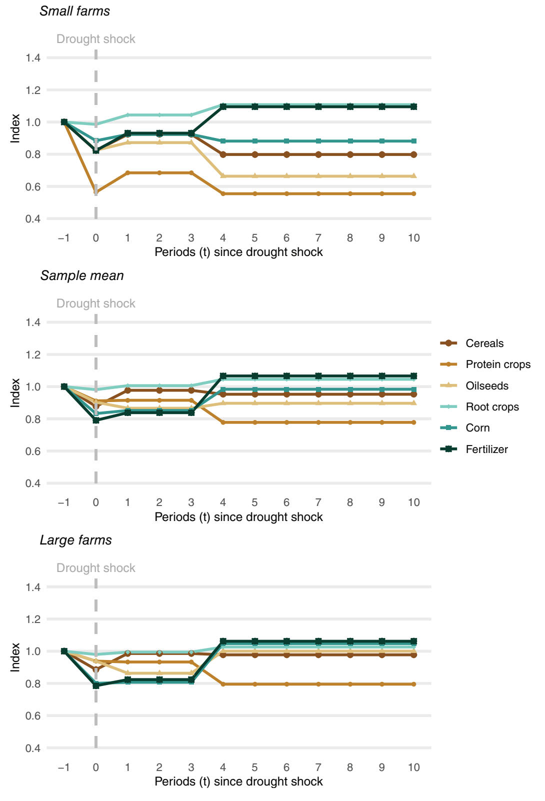

FIGURE 4 Simulated changes in crop supply and fertilizer demand after a drought occurring in $t=0$, across heterogeneous farm sizes. Small (large) farms are defined as farms endowed with less (more) than the median number of hectares (106 ha) in our sample.

structure, the relative changes and medium-term adjustments in crop supply and fertilizer demand are robust across all specifications.

Second, we changed the functional forms of the weather variables and included squared terms for observed and past growing degree days and precipitation (see Data S6.4). Again, the price and weather elasticities at the sample mean are similar to those in the main specification. A slight difference is observed in the simulation results, in which protein production is not detrimentally affected in the drought year. Overall, adjustments in crop supplies and input demand in the years following the drought shock are not affected by the inclusion of the squared weather terms.

Third, we tested the robustness of the results to the imposition of curvature on the profit function. As already discussed, the unrestricted estimation of the system of output supply and input demand functions resulted in output supply functions that are nondecreasing in own prices and input demand functions that are nonincreasing in own prices, as required by economic theory. However, the unrestricted model does not fulfill the convexity condition of the profit function, as indicated by a non-semi definite Hessian matrix. The convexity of the profit function reflects that farmers can take advantage of favorable price changes by adjusting output and input combinations for the profit to increase more than proportionally to price changes. To check whether our results are sensitive to the imposition of convexity, we estimated a restricted version of the model, in which convexity is imposed using Cholesky factorization. For this purpose, the Hessian matrix $\boldsymbol{B}$ of the normalized quadratic profit function with respect to prices is rewritten as $\boldsymbol{B}=\boldsymbol{L}\boldsymbol{L}'$, where $\boldsymbol{L}$ is the lower triangular matrix holding the parameters to be estimated. As four of the six eigenvalues of the Hessian matrix are non-negative in the unrestricted version, we estimated the Cholesky factorization with rank = 4 (Diewert & Wales, 1988; Moschini, 1998). To facilitate convergence of this highly nonlinear model, we divided all variables by their sample mean prior to the estimation. Furthermore, we had to drop the interaction terms between the observed and past weather variables to keep the estimation and bootstrapping within a manageable time. As shown in Data S6.5, the estimates of price elasticities and weather semi-elasticities are similar across both models, confirming that the imposition of convexity is in accordance with the data. The simulation exercise shows that the production responses to a drought shock based on the restricted estimation are very similar to those indicated by the unrestricted estimation.

6 | CONCLUSION

This study assessed farmers' responses in crop supply and input demand to weather trends. The theoretical framework shows that expected weather affects production choices through the allocation of fixed inputs, whereas realized weather affects output directly through yield effects and indirectly through farmers' input adjustments. Based on this conceptual framework, we empirically estimated the farms' output supply and input demand as functions of both expected and realized weather. This structural modeling approach captures the trade-off in the production of different crops, which arises from farmers' optimal resource allocation across individual crops. Optimal resource allocation depends on the relative profitability of the crops, which is influenced by expected and realized weather outcomes. The estimated parameters were then used to simulate the immediate and lasting effects of drought events on farmers' production decisions.

The results reveal heterogeneous effects of weather trends on the supply of individual crops. For instance, an increase in the number of growing degree days shifts production from cereals and oilseeds toward root crops. The simulation exercise suggests that drought events result in a reduced supply of protein crops, cereals, oilseed crops, and corn, as well as in reduced fertilizer use. Corn is the crop that suffers the most (−20% based on our baseline model) in the drought year. In subsequent years, the supply of protein crops reduces to less than 20% below the original levels, and roots crop production tends to increase. Fertilizer demand is decreased both in the year of the shock and in subsequent years. Hence, an extreme weather event has immediate and lasting effects on farmers' production choices. We also found that smaller farms are more affected by the drought shock than larger ones, both in the year of the extreme event and in subsequent years.

A limitation of our study is the assumption of risk neutrality of farmers in the profit maximization approach. Although this assumption is commonly made in the agricultural economics literature, it may be challenged, as farmers have been found to be generally risk and loss averse (Rommel et al., 2022). Chambers and Quiggin (2000) showed that the duality between farmers' profit and production functions holds under risk and uncertainty in a state-contingent framework. However, the empirical assessment of farmers' decisions in this framework requires data under different states of nature (e.g., Serra et al., 2010; Sidhoum et al., 2020), although only one state of nature is observed in reality. Hence, we focused on the profit maximization approach in this study and leave the extension to flexible risk preferences for future work. We also note that profit maximization can be a reasonable assumption if farmers have access to functioning financial markets and off-farm work (Chambers & Voica, 2017), which might well be the case in our empirical case of Germany.

The results of this study have several important policy implications. First, they provide evidence that changes in both realized and expected weather are important determinants of crop-specific output supply as well as input demand. This finding underscores that the evaluation of the impact of weather and climate on agricultural production must go beyond pure yield effects and consider farm-level adjustments in output supply and input demand. Second, transformative events (e.g., droughts) have lasting effects on farmers' production decisions. In our empirical application, the supply of protein crops decreased considerably after a simulated drought shock and remained below previous levels. However, it is an important topic on the policy agenda of the EU and other regions to enhance domestic protein crop production due to their environmental benefits (Bues et al., 2013). Extreme events, which become more frequent under climate change (e.g., Robinson et al., 2021), may undermine such policy goals, and therefore, additional incentives may be necessary. More generally, this result implies that transformative events must be considered in addition to gradual changes in temperature and precipitation when assessing the effects of climate change on agricultural production.

Third, extreme weather affects fertilizer use, which has significant environmental implications. In particular, we found that farmers respond to drought events by reducing fertilizer application. This behavior is economically rational, as the ability of plants to take up nitrogen is reduced under suboptimal growing conditions. Therefore, the provision of detailed and real-time information about the growth potential of crops can help farmers align fertilizer usage with nitrogen uptake, which is important from both economic and ecological perspectives.

Although this study focused on the net effect of weather trends on farm-level output supply and input demand, further research in this area may disentangle the yield effects from the reallocation of fixed allocatable inputs. Such insights can inform researchers and policy makers about the relative importance of yield impacts and adaptation behavior. On the variable input side, our study focused on fertilizer use. An extension of this model could focus on pesticide use, which has been found to be affected by extreme weather events (Möhring et al., 2022). For this purpose, pesticide use could be incorporated into the profit maximization problem as a damage-control agent (see, e.g., Chatzimichael et al., 2022; Lichtenberg & Zilberman, 1986). Finally, further research is required with respect to the heterogeneous effects of weather and climate, not only across farm sizes in terms of area of farmed land as in this study but also across different farm types (e.g., crop farms vs. livestock farms) and regions. Understanding the heterogeneity of farm vulnerability and adaptation capacities is essential for policymakers and other stakeholders to minimize the detrimental effects of weather shocks and climate change on agricultural production.

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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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APPENDIX A

TABLE A1 Estimated parameters of the first-stage probit regressions.

Variable	Cereals	Protein crops	Oilseeds	Root crops	Corn
Intercept	−2.208	−1.858	5.669***	0.156	13.928***
	(−13.976; 13.764)	(−5.323; 2.270)	(1.188;10.350)	(−6.283; 6.480)	(8.898; 20.198)
P cereals	0.778	−5.881***	1.774*	−5.605***	3.701***
	(−5.142; 8.709)	(−8.391; −3.498)	(−0.037; 3.616)	(−8.093; −3.160)	(1.956; 5.677)
P protein	0.496	0.683	0.457	−0.946	0.199
	(−1.123; 2.093)	(−0.400; 1.662)	(−0.072; 1.006)	(−1.988; 0.342)	(−0.426; 0.860)
P oilseed crops	−1.837	−1.985***	1.629***	0.488	−0.391
	(−5.203; 1.173)	(−3.276; −0.798)	(0.760; 2.563)	(−0.441; 1.458)	(−1.338; 0.565)
P root crops	−4.795*	−1.400	−1.428	3.359***	−2.561**
	(−10.557; 0.787)	(−4.446; 2.193)	(−4.223; 1.228)	(1.357; 5.315)	(−5.280; −0.251)
P corn	0.950*	−0.194	−0.052***	−0.038	0.024
	(−0.003; 5.745)	(−0.814; 0.058)	(−0.245; −0.008)	(−0.121; 0.031)	(−0.114; 0.103)
R fert	−0.077	−0.042	0.121***	−0.055	0.142***
	(−0.392; 0.223)	(−0.134; 0.052)	(0.044; 0.202)	(−0.150; 0.021)	(0.055; 0.226)
K land	0.008***	0.001***	0.002**	0.001***	0.001***
	(0.003; 0.030)	(3e−04; 0.002)	(1e−04; 0.005)	(3e−04; 0.003)	(5e−04; 0.003)
K labor	−0.029**	−0.020	−0.011	0.061*	−0.014
	(−0.112; −1e−05)	(−0.104; 0.031)	(−0.071; 0.032)	(−0.012; 0.143)	(−0.094; 0.022)
K capital	−0.001	3e−05	1e−04	−3e−05	6e−05
	(−0.002; 4e−04)	(−1e−04; 2e−04)	(−1e−04; 4e−04)	(−5e−04; 2e−04)	(−1e−04; 2e−04)
Trend	−0.108	−0.044*	0.138***	−0.029	−0.031
	(−0.306; 0.040)	(−0.101; 0.006)	(0.091; 0.189)	(−0.077; 0.025)	(−0.080; 0.016)
Trend^2	0.004	0.002*	−0.004***	−3e−04	0.005***
	(−0.001; 0.011)	(−1e−04; 0.004)	(−0.005; −0.002)	(−0.002; 0.001)	(0.003; 0.006)

(Continues)

TABLE A1 (Continued)

Variable	Cereals	Protein crops	Oilseeds	Root crops	Corn
L.share cereals	0.800	0.304	1.711***	−0.191	−6.273***
	(−0.628; 1.991)	(−0.457; 1.189)	(1.119; 2.295)	(−0.870; 0.500)	(−8.663; −3.165)
L.share protein cr.	0.316	8.109***	1.414**	−0.679	−6.968***
	(−1.122; 4.482)	(5.082; 10.999)	(0.289; 2.637)	(−1.562; 0.238)	(−9.457; −4.185)
L.share oilseeds	3.709***	−0.067	2.887***	−0.281	−6.367***
	(1.373; 8.710)	(−0.876; 0.838)	(2.153; 3.695)	(−1.098; 0.388)	(−8.777; −3.609)
L.share root cr.	−0.658	0.650	−0.982**	20.772***	−5.952***
	(−2.219; 1.097)	(−0.898; 2.064)	(−1.980; −0.215)	(12.188; 28.537)	(−8.196; −3.250)
Gdd1to3	−3e−04	−0.001	−0.006***	−3e−04	−0.001*
	(−0.004; 0.005)	(−0.002; 0.001)	(−0.007; −0.004)	(−0.002; 0.001)	(−0.003; 2e−04)
Prec1to3	0.002	0.003**	−0.002	−0.001	−8e−05
	(−0.005; 0.008)	(0.001; 0.005)	(−0.004; 0.001)	(−0.003; 0.001)	(−0.002; 0.002)
GddHigh1to3	0.016	−0.022	0.036***	0.006	−0.064***
	(−0.068; 0.082)	(−0.056; 0.015)	(0.010; 0.064)	(−0.025; 0.039)	(−0.096; −0.036)
DD1to3	0.001	0.041***	−0.004	0.003	−0.001
	(−0.037; 0.035)	(0.030; 0.054)	(−0.015; 0.007)	(−0.007; 0.015)	(−0.011; 0.010)
Gdd4to10	0.005	−0.002	−0.009***	−0.001	0.003
	(−0.008; 0.022)	(−0.006; 0.002)	(−0.014; −0.005)	(−0.006; 0.003)	(−0.001; 0.007)
Prec4to10	0.003	0.008***	−0.008***	−0.001	−2e−04
	(−0.011; 0.018)	(0.004; 0.013)	(−0.012; −0.003)	(−0.005; 0.004)	(−0.004; 0.004)
GddHigh4to10	−0.016	0.022	0.103**	0.025	−0.131**
	(−0.289; 0.201)	(−0.052; 0.102)	(0.017; 0.180)	(−0.071; 0.119)	(−0.231; −0.042)
DD4to10	−0.040	0.078***	−0.046***	−0.011	−0.020
	(−0.144; 0.053)	(0.055; 0.110)	(−0.074; −0.019)	(−0.039; 0.023)	(−0.048; 0.010)

Note: Estimation is based on 14,796 observations. Each column presents an individual regression. The dependent variables are binary variables that take the value 1 if the particular crop is grown and 0 otherwise. 95% confidence intervals, presented in parentheses, are obtained using nonparametric bootstrapping with $n = 1000$.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE A2 Regression diagnostics of the profit system.

Dependent variable	Estimated parameters	Root mean square error	R^2
Cereals supply	64	4512.04	0.91
Protein crops supply	64	382.95	0.68
Oilseeds supply	64	1078.46	0.80
Root crops supply	64	10912.57	0.60
Corn supply	64	7432.71	0.31
Fertilizer demand	63	60.30	0.79

Note: Estimation is based on 14,796 observations.

TABLE A3 Parameter estimates for the profit system.

Variable	Coeff.	95% CI	Variable	Coeff.	95% CI
Cereals supply			*Root crops supply*		
Intercept	−158987.03***	(−296220.81; −36661.23)	Intercept	−343842.64	(−930926.34; 180604.77)
P cereals	24827.59***	(20269.53; 29369.14)	P cereals	884.70	(−1412.04; 3181.85)
P protein	699.70	(−898.55; 2154.95)	P protein	4156.58**	(984.08; 7526.16)
P oilseed crops	3631.74***	(2437.01; 5035.24)	P oilseed crops	−524.03	(−1966.94; 994.57)
P root crops	884.70	(−1412.04; 3181.85)	P root crops	16426.71**	(1258.49; 32373.56)
P corn	4.90	(−14.60; 24.32)	P corn	108.27	(−71.88; 278.64)
R fert	−396.09***	(−464.29; −335.34)	R fert	21.90	(−33.39; 73.59)
Z land	35.29***	(23.88; 46.45)	Z land	15.27*	(−1.86; 37.86)
Z labor	71.50	(−102.71; 277.77)	Z labor	−165.11	(−634.26; 573.69)
Z capital	0.54	(−0.03; 0.96)	Z capital	3.19**	(0.37; 6.93)
Trend	452.69***	(359.11; 539.65)	Trend	−592.90***	(−960.65; −189.73)
Trend^2	−15.62***	(−18.78; −11.86)	Trend^2	37.45***	(21.62; 51.67)
Gdd	−6.30*	(−13.95; 0.65)	Gdd	11.24	(−9.90; 32.46)
Prec	−13.05***	(−17.49; −8.09)	Prec	13.24	(−3.79; 30.93)
GddHigh	76.39***	(44.28; 109.83)	GddHigh	−430.03***	(−530.66; −313.84)
DD	204.97***	(106.09; 316.02)	DD	289.06	(−143.40; 714.12)
Gdd1to3	−12.22**	(−22.36; −1.89)	Gdd1to3	14.02	(−27.27; 53.78)
Prec1to3	12.24***	(5.35; 19.02)	Prec1to3	29.47**	(1.11; 55.35)
GddHigh1to3	−10.68	(−64.03; 38.14)	GddHigh1to3	−596.35***	(−838.40; −302.04)
DD1to3	−140.82***	(−217.00; −65.02)	DD1to3	−117.08	(−414.36; 192.79)
Gdd4to10	−10.07**	(−19.81; −0.86)	Gdd4to10	109.18***	(70.40; 143.94)
Prec4to10	−16.96***	(−26.34; −8.09)	Prec4to10	57.13***	(15.26; 106.59)
GddHigh4to10	187.58***	(55.00; 313.15)	GddHigh4to10	−2331.56***	(−3200.41; −1508.49)
DD4to10	388.15***	(273.79; 503.43)	DD4to10	484.72**	(75.76; 918.83)
Gdd x Gdd1to3	0.01**	(1e−03; 0.02)	Gdd x Gdd1to3	0.01	(−0.03; 0.05)
Prec x Prec1to3	−0.01	(−0.03; 4e−03)	Prec x Prec1to3	−0.03	(−0.09; 0.05)

TABLE A3 (Continued)

Variable	Coeff.	95% CI	Variable	Coeff.	95% CI
GddHigh x GddHigh1to3	0.34	(−2.74; 3.66)	GddHigh x GddHigh1to3	−3.31	(−16.40; 7.19)
DD x DD1to3	1.46***	(0.78; 2.16)	DD x DD1to3	1.30	(−1.59; 3.91)
Gdd x Gdd4to10	−0.01**	(−0.02; −1e−03)	Gdd x Gdd4to10	−0.02	(−0.05; 0.01)
Prec x Prec4to10	0.05***	(0.03; 0.06)	Prec x Prec4to10	−0.02	(−0.10; 0.06)
GddHigh x GddHigh4to10	−13.56***	(−19.97; −7.02)	GddHigh x GddHigh4to10	30.66***	(13.39; 49.34)
DD x DD4to10	−3.43***	(−4.41; −2.49)	DD x DD4to10	−3.55**	(−7.05; −0.18)
φ Cereals	−1556.54	(−4214.28; 1400.34)	φ Roots	−18401.64***	(−21620.09; −15297.47)
Protein crops supply			*Corn supply*		
Intercept	−7148.82	(−62263.96; 35488.05)	Intercept	364030.79	(−401591.19; 1089074.18)
P cereals	699.70	(−898.55; 2154.95)	P cereals	4.90	(−14.60; 24.32)
P protein	125.23	(−1152.60; 1363.57)	P protein	32.59***	(13.26; 1459.86)
P oilseed crops	2135.86***	(1017.68; 3245.14)	P oilseed crops	−4.79	(−462.34; 36.63)
P root crops	4156.58**	(984.08; 7526.16)	P root crops	108.27	(−71.88; 278.64)
P corn	32.59***	(13.26; 1459.86)	P corn	63.45	(−105.94; 240.55)
R fert	−20.13*	(−42.07; 0.55)	R fert	0.42**	(0.05; 0.80)
Z land	2.03	(−1.14; 3.89)	Z land	−15.68	(−60.71; 20.78)
Z labor	−60.35	(−171.47; 87.19)	Z labor	−10.44	(−438.15; 559.13)
Z capital	0.01	(−0.49; 0.31)	Z capital	−2.01*	(−4.42; 0.83)
Trend	73.18	(−14.46; 148.45)	Trend	801.45	(−476.83; 2274.29)
Trend^2	−2.56	(−5.66; 1.22)	Trend^2	−4.15	(−35.50; 25.57)
Gdd	0.80	(−6.26; 9.44)	Gdd	−59.33	(−155.19; 10.04)
Prec	−0.48	(−4.71; 3.97)	Prec	57.13*	(−5.52; 133.73)
GddHigh	24.85	(−21.21; 67.56)	GddHigh	−130.90	(−358.67; 102.23)
DD	−42.53	(−123.39; 57.83)	DD	935.12	(−289.18; 2362.94)
Gdd1to3	1.05	(−8.13; 11.94)	Gdd1to3	−60.97	(−160.70; 19.27)
Prec1to3	−3.64	(−12.24; 5.25)	Prec1to3	5.41	(−144.36; 109.63)
GddHigh1to3	19.53	(−48.02; 82.86)	GddHigh1to3	−317.09	(−764.67; 167.04)

(Continues)

TABLE A3 (Continued)

Variable	Coeff.	95% CI	Variable	Coeff.	95% CI
DD1to3	−4.14	(−106.84; 90.18)	DD1to3	377.46	(−765.36; 1929.94)
Gdd4to10	−8.25	(−21.80; 3.41)	Gdd4to10	−15.01	(−227.23; 151.40)
Prec4to10	14.73**	(2.50; 26.00)	Prec4to10	−25.35	(−141.42; 114.71)
GddHigh4to10	73.96	(−62.16; 224.52)	GddHigh4to10	−1004.60	(−2361.89; 265.35)
DD4to10	−6.35	(−133.15; 141.04)	DD4to10	−101.06	(−1966.78; 1915.70)
Gdd x Gdd1to3	−4e−03	(−0.02; 0.01)	Gdd x Gdd1to3	0.06	(−0.03; 0.13)
Prec x Prec1to3	0.02	(−0.01; 0.04)	Prec x Prec1to3	−0.08	(−0.23; 0.12)
GddHigh x GddHigh1to3	0.43	(−6.47; 7.83)	GddHigh x GddHigh1to3	−23.41	(−80.90; 11.11)
DD x DD1to3	0.04	(−0.81; 0.97)	DD x DD1to3	−4.22	(−21.24; 7.47)
Gdd x Gdd4to10	1e−03	(−0.01; 0.01)	Gdd x Gdd4to10	−5e−03	(−0.11; 0.10)
Prec x Prec4to10	−0.02	(−0.04; 0.01)	Prec x Prec4to10	−0.12	(−0.56; 0.17)
GddHigh x GddHigh4to10	0.36	(−14.36; 13.73)	GddHigh x GddHigh4to10	17.91	(−25.55; 74.37)
DD x DD4to10	0.22	(−0.91; 1.17)	DD x DD4to10	−3.80	(−15.43; 7.32)
φ Protein	−615.43***	(−757.80; −385.19)	φ Corn	−5906.84***	(−9129.65; −3786.65)
Oilseeds supply			*Fertilizer demand (negative)*		
Intercept	−50827.42***	(−86219.31; −17827.42)	Intercept	2014.27***	(840.14; 3288.85)
P cereals	3631.74***	(2437.01; 5035.24)	P cereals	−396.09***	(−464.29; −335.34)
P protein	2135.86***	(1017.68; 3245.14)	P protein	−20.13*	(−42.07; 0.55)
P oilseed crops	5391.34***	(4018.95; 6612.22)	P oilseed crops	156.28***	(123.58; 187.61)
P root crops	−524.03	(−1966.94; 994.57)	P root crops	21.90	(−33.39; 73.59)
P corn	−4.79	(−462.34; 36.63)	P corn	0.42**	(0.05; 0.80)
R fert	156.28***	(123.58; 187.61)	R fert	1.84	(−0.76; 4.37)
Z land	7.55***	(3.22; 12.11)	Z land	−0.32***	(−0.46; −0.16)
Z labor	−98.01	(−291.35; 92.77)	Z labor	−1.60	(−5.80; 1.65)
Z capital	−0.03	(−0.26; 0.15)	Z capital	−2e−03	(−0.01; 0.01)
Trend	261.40***	(195.70; 320.94)	Trend	−10.83***	(−13.02; −9.00)
Trend^2	−7.98***	(−10.16; −6.09)	Trend^2	0.45***	(0.37; 0.53)

TABLE A3 (Continued)

Variable	Coeff.	95% CI	Variable	Coeff.	95% CI
Gdd	−2.11	(−5.53; 1.62)	Gdd	0.10	(−0.04; 0.26)
Prec	−4.10***	(−7.03; −1.41)	Prec	−0.21***	(−0.29; −0.15)
GddHigh	27.60**	(5.86; 49.96)	GddHigh	−1.44***	(−1.91; −1.01)
DD	−20.08	(−88.56; 58.11)	DD	4.76***	(2.25; 7.00)
Gdd1to3	−1.50	(−8.17; 5.06)	Gdd1to3	0.40***	(0.17; 0.66)
Prec1to3	0.38	(−3.78; 4.89)	Prec1to3	−0.12	(−0.28; 0.04)
GddHigh1to3	23.85	(−14.51; 63.30)	GddHigh1to3	2.33***	(0.83; 3.68)
DD1to3	−106.70***	(−164.15; −45.23)	DD1to3	4.83***	(3.35; 6.30)
Gdd4to10	−11.06***	(−18.22; −3.66)	Gdd4to10	−0.28***	(−0.46; −0.12)
Prec4to10	−16.81***	(−23.46; −10.57)	Prec4to10	−0.05	(−0.24; 0.15)
GddHigh4to10	51.37	(−45.28; 162.46)	GddHigh4to10	2.11*	(−0.18; 4.42)
DD4to10	46.44	(−27.78; 129.91)	DD4to10	−0.06	(−2.33; 1.96)
Gdd x Gdd1to3	−1e−03	(−0.01; 0.01)	Gdd x Gdd1to3	−3e−04***	(−5e−04; −8e−05)
Prec x Prec1to3	−3e−03	(−0.01; 0.01)	Prec x Prec1to3	3e−04	(−1e−04; 7e−04)
GddHigh x GddHigh1to3	−0.74	(−3.14; 2.15)	GddHigh x GddHigh1to3	−0.03	(−0.10; 0.05)
DD x DD1to3	0.86***	(0.34; 1.33)	DD x DD1to3	−0.05***	(−0.06; −0.03)
Gdd x Gdd4to10	2e−03	(−4e−03; 0.01)	Gdd x Gdd4to10	3e−04***	(1e−04; 4e−04)
Prec x Prec4to10	0.01*	(−2e−03; 0.02)	Prec x Prec4to10	3e−04	(−1e−04; 7e−04)
GddHigh x GddHigh4to10	−2.84	(−9.39; 3.08)	GddHigh x GddHigh4to10	0.16***	(0.04; 0.27)
DD x DD4to10	−0.78**	(−1.44; −0.20)	DD x DD4to10	−1e−03	(−0.02; 0.02)
φ Oilseed	−542.01***	(−700.01; −371.11)			

Note: Estimation is based on 14,796 observations. The system of equations is estimated as seemingly unrelated regression (SUR) using the *systemfit* (Henningsen and Hamann, 2007) package in R. The φ's are obtained from first-stage probit regressions for each crop. 95%-confidence intervals, presented in parentheses, are obtained using non-parametric bootstrapping with $n = 1000$.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.