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Weather impacts and input adaptation: farm-level evidence on corn and wheat yields in italy

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Abstract

The objective of this paper is to evaluate how weather affects Italian corn and wheat yields and to assess the short-run input adaptation behaviour of farmers using a recently proposed structural model that incorporates fertilizer and pesticide use. In this way, we are able to distinguish between the 'direct' weather effects (i.e. the agronomic impacts of weather changes on plant growth) and the 'indirect' effects mediated through farmers' input choices (i.e. adaptation impacts). We use a large representative panel dataset of Italian corn and common wheat producers covering the period from 2008 to 2022 sourced from the Italian Farm Accountancy Data Network (FADN), matched with data on temperatures and precipitation at a high spatial and temporal resolution. Our results indicate that corn is vulnerable to temperature increases and we find significant damages already at the sample median temperature, while we find no significant negative effects of temperature increases on wheat yields at the sample median temperature. We show that farmers do adapt their fertilizer and pesticide use to in-season temperature shocks, but with varying effects depending on the crop. At the sample median temperature, adaptation through input use reduces by approximately 11 per cent the direct agronomic negative effects for corn and provides a small positive effect for wheat. Scenario analysis shows significant yield reductions for corn and no reductions for wheat in 2050. However, for non-marginal temperature increases, the input adaptation effect declines for both crops, highlighting the need for alternative and complementary adaptation strategies in the long term.

Keywords weather impacts, climate change, structural modelling, adaptation, agricultural inputs, italian agriculture

JEL codes Q11, Q15, Q51, Q54

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1. Introduction

Weather realizations are undoubtedly one of the key determinants of agricultural production. With climate change altering weather patterns across the globe, understanding the relationship between weather variability and crop yields has become increasingly important to inform adaptation strategies in the agricultural sector and to predict expected damages more accurately (Auffhammer and Schlenker 2014). An extensive and growing body of literature therefore examines how weather and climate conditions, particularly temperature, affect crop yields (see Ortiz-Bobea 2021, for a comprehensive overview). The relationship between weather and yield is commonly estimated by means of a reduced-form panel approach consisting of regressing crop yields on growing season weather conditions, controlling for individual fixed effects. Deviations from average yields are thus attributed to deviations from average weather conditions (Mérel and Gammans 2021). The assumption of causality in these models relies on the fact that certain farming decisions—such as crop choice, parcel selection, and acreage—are made before growing season weather realizations and are therefore independent from actual weather realizations.

A prominent question in this literature is the extent to which farmers adapt to climate change and if this adaptation is captured by panel estimates that use yearly variation and under which conditions (Mérel and Gammans 2021; Lemoine 2021). A recent contribution is given by Hultgren et al. (2025), who exploit these conditions and infer long-run adaptation to climate change using reduced-form statistical techniques. However, besides long-run adaptation to climate (for instance, through crop switching, improved varieties, or investments in irrigation), farmers are also expected to adapt to adverse weather conditions during the growing season by modifying other agricultural practices like input use behaviour (Chen and Gong 2021) or cropping practices (Ramsey et al. 2021). As a consequence, studies employing panel data and fixed-effects interpret their results as including short-run in-season adaptation in their estimates (Blanc and Schlenker 2017). Still, the actual extent and impact of this short-run adaptation, such as adjustments in fertilizer and pesticide use, is rarely quantified or explicitly investigated. A recent exception is Bareille and Chakir (2024), who estimate a structural model of crop production incorporating input adjustments using a sample of French farms. They demonstrate that farmers do adapt to weather conditions through their input use behaviour during the growing season and confirm that standard reduced-form panel models capture this effect in their estimates.

Starting from this background, our paper aims to quantify the short-run input adaptation of corn and common wheat producers in Italy, focusing on adjustments in fertilizer and pesticide use within the growing season, using a structural model based on Bareille and Chakir (2024) estimated using farm-level data obtained from the Italian Farm Accountancy Data Network (FADN). We focus on corn and common wheat since these are two of the most important cereal crops cultivated in Italy.[1]

While much of the literature on the impact of climate change on European agriculture relies on biophysical crop models, which predict significant damage in Southern Europe (e.g. JRC Peseta IV—Hristov et al. 2020), econometric models based on observational data remain limited, especially for the Mediterranean region and at subnational scales. A few studies have addressed the impacts of climate change on Italian agriculture, with sectoral studies under a high-emission scenario (RCP 8.5) predicting a 12 per cent reduction in farmland value (Bozzola et al. 2018) and a 22 per cent decline in Gross Value Added (GVA) per worker (Olper et al. 2021). Using farm-level data, Coderoni and Pagliacci (2023) find that considering changes in medium and long-term climate, land productivity is negatively impacted by higher temperatures in the colder seasons and in spring, and larger spring cumulative rainfall.

Regarding crop-level studies of Italian agriculture, there are currently only a few contributions and a notable gap in the literature. Accetturo and Alpino (2023) address weather impacts on corn, durum wheat, and grapevine production at the province level using a piecewise specification with Growing Degree Days. For corn, they find the upper temperature threshold to be at 29°C, above which the effect on yields is negative. Chavas et al. (2019) use corn and wheat yields in seven Italian regions over a long time period (1900–2014) for the empirical estimation and employ a quantile autoregression model to assess the effects of weather on the distribution of yields. The paper finds that the effects are asymmetric, with larger impacts on the lower tail, and that yields in Italy exhibit slow dynamic adjustments to inter-annual temperature changes, suggesting that weather has long-term effects. A subsequent study (Chavas et al. 2022) then analyses corn and wheat yields and production risk distribution over time and space to assess the linkages with Italian food security using a dataset similar to the one employed in their previous work. Other studies focus instead on durum wheat production. Tappi et al. (2022) find that durum yields react negatively to precipitation and show an inverted-U relationship with maximum temperatures. Tappi et al. (2023) then further explore the heterogeneity along the growing season of the impacts of weather shocks on yields of different durum wheat varieties. While these studies provide interesting contributions, they overall answer different research questions from the one we are interested in, and none of them uses data at the farm level for the estimation.

The novelty of our study lies in the fact that we do not just model the relationship between yields and weather conditions, but we also include the input use adaptation behaviour of farmers by employing a structural model estimated using farm-level production data. As discussed in Timmins and Schlenker (2009), the use of structural models is still limited in environmental and resource economics. There is, however, a high level of complementarity with reduced form models, and the two methods can be used in conjunction with one another to investigate the same question under different perspectives and to provide stronger support to the empirical estimations (Low and Meghir 2017). Our study, therefore, aims to provide relevant insights for the understanding of the adaptation behaviour of the Italian farmers and for the development of more accurate crop-level climate change projections for the major crops cultivated in Italy.

We make three key contributions to the literature. First, to date, no study has estimated a comprehensive econometric crop model (whether reduced-form or structural) using farm-level data for Italy. As one of the most important agricultural producers in the European Union (EU), both in terms of output and number of farms (CREA 2024), understanding Italian crops' vulnerability and potential for adaptation to climate change has significant implications for the EU agricultural adaptation policy. Second, to our knowledge, a structural model to estimate the yield-temperature relationship and input adaptation for corn has not been applied yet. Corn is a critical global crop and has been extensively studied in the empirical climate-agriculture literature (see Schlenker and Roberts 2006, for an early example). Moreover, compared to wheat, which is a C3 crop, corn is a C4 crop (i.e. follows a different photosynthetic pathway) and is cultivated in Italy during the summer growing season. Understanding whether farmers adapt their behaviour during the growing season and if reduced-form approaches capture short-run adaptation for these crops is crucial for advancing the broader literature on climate change impacts and adaptation. Third, while the study by Bareille and Chakir (2024) offers valuable insights using data from a specific French region (Meuse, in the north of France), its external validity has not been tested across a larger, more representative sample. Their analysis is based on a smaller sample of farmers from a specific provider, while our study instead uses data from a significantly larger pool representative of Italian farmers sourced from the EU FADN. This will help assess the broader applicability of their framework and possibly encourage similar analysis in other European countries exploiting FADN data.

Our results indicate that in Italy both crops show a concave relationship of yields with respect to temperature, and that corn production is more vulnerable to increases in temperature than wheat. At the sample median temperature, there are statistically significant negative impacts on corn yields, while wheat yields are not significantly affected. We find that wheat's sensitivity to temperature increases is indeed quite small. Importantly, we find evidence of input adaptation during the growing season for corn, which effectively mitigates a sizeable part of the agronomic impacts on plant growth. At the sample median temperature, input adaptation reduces by more than 10 per cent the damage of a 1 per cent temperature increase. These findings suggest a relevant adaptation potential for corn, which however diminishes for warmer places (with temperature higher than the median). Regarding wheat instead, our results indicate an effect on input behaviour, which results in a positive effect on yields. However, wheat yields are overall less sensitive to temperature increases, and the marginal productivity of fertilizers and pesticides is lower for wheat than for corn. Our findings imply that fertilizer and pesticide management can indeed be used to offset some of the damage to crop production from increasing temperatures. At the same time, simulations of the agronomic and adaptation effect under the SSP3-7.0 scenario for 2050 show a modest and non-significant adaptation effect. Given that the adaptation potential declines at higher temperature levels, input use adjustment does not seem to be effective or efficient as a long-term adaptation strategy, underscoring the importance of deploying other adaptation strategies as well.

These results are quite relevant to ongoing debates and policy developments regarding the sustainability and resilience of the European agricultural sector and underscore the importance of incorporating climate adaptation considerations into agricultural policy. Agricultural input management receives considerable public attention and is a central topic in landmark policies, like the Farm to Fork strategy proposed in 2020, which aims to reduce the use of pesticides by 50 per cent and of fertilizers by 20 per cent by 2030 (Schebesta and Candel 2020; Gohin 2024). Moreover, an increasingly uncertain geopolitical context and the reliance of the EU on fertilizer imports from third countries raise further concerns about the resilience of agricultural production and its adaptation capacities (Loi et al. 2024). Our analysis finds that farmers currently rely on fertilizers and pesticides as an adaptation strategy against weather stress. This highlights a possible trade-off: while reducing input use is essential for environmental sustainability and to reduce environmental degradation, it may conflict with short-term adaptation needs, potentially leaving farmers more vulnerable to climate variability.

The paper is organized as follows. Section 2 introduces the conceptual framework and Section 3 the empirical strategy. Section 4 presents the data used in the analysis and summary statistics. Section 5 compares the results of the models and describes the results we obtained. Section 6 provides the conclusion.

2. Conceptual framework

Following the approach introduced by Bareille and Chakir (2024), we compare a reduced form model of crop yields along the lines of the core literature (Schlenker and Roberts 2009; Burke and Emerick 2016; Mérel and Gammans 2021; Ortiz-Bobea 2021) with a structural model where changes in inputs (fertilizers and pesticides) use are directly considered in the estimation. The former reduced form model can be interpreted as modelling crop yields on non-linear functions of the weather variables with farm fixed effects:

$$y_{i,t} = f(T_{i,t}) + g(P_{i,t}) + \alpha_i + \varepsilon_{i,t}, \tag{1}$$

where $y_{i,t}$ is the yield for farm i, in year t. $f(T_{i,t})$ is a non-linear function of temperature during the crop-specific growing season, and $g(P_{i,t})$ is a non-linear function of precipitation during the growing season. α_i represents farm fixed effects to account for time-invariant farm heterogeneity. Finally, $\varepsilon_{i,t}$ is an i.i.d. error term. The inclusion of the unit fixed effects implies that the identi-

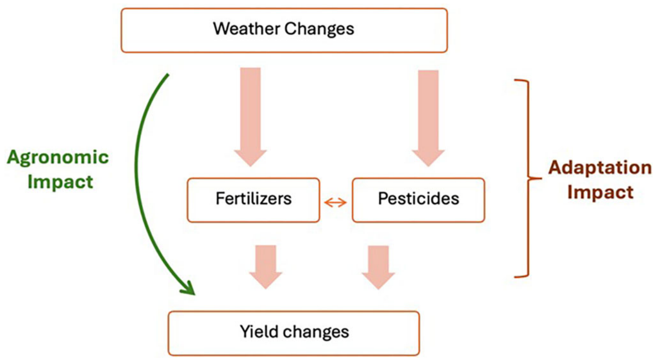

Figure 1 Impact of weather on yield accounting for input adaptation.

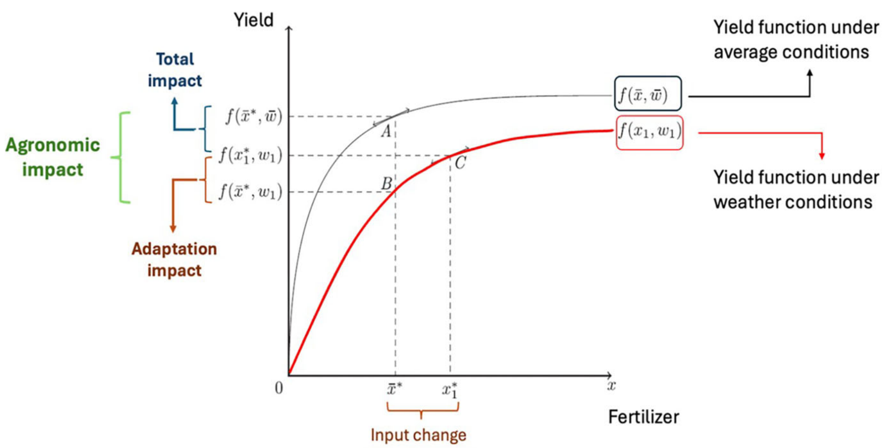

Figure 2 Crop production under changing weather conditions. Single input case. *Notes:* adapted from Bareille and Chakir (2024).

fication comes from the within-farm annual deviation from the average weather. This variation is plausibly random and exogenous, and the associated coefficients of weather variables can be reasonably interpreted as causal effects. As noted before, given that farmers can modify certain agricultural practices within the growing season, this fixed effects model is typically interpreted as including short-run adaptation in the considered estimates (Blanc and Schlenker 2017). This means that the weather effects estimated by this model should be comparable to the weather effects derived from the structural model that explicitly accounts for this kind of adaptation.

The structural approach likewise models crop yields on weather conditions during the growing season, but it further allows to simultaneously and separately measure: *i.* the direct impact of weather changes on crop yields, independently of farmers' adaptation (i.e. the agronomic impact); *ii.* the farmers' response to weather changes through modifications in practices (i.e. the change in inputs use); *iii.* the consequences of these adaptations on crop yields (i.e. the short-run adaptation impact). Figure 1 provides a graphical representation of the process.

In Figure 2, we characterize the logic of this approach in a simplified way as a comparative statics exercise with a single input (e.g. fertilizer). Yield is a function of fertilizer (x) and weather (w), i.e. $yield = f(\bar{x}, \bar{w})$ under average weather conditions and use of fertilizer (black line). For a rational farmer at given market prices, point A represents the optimal production level. He will choose the $\bar{x}^*$ optimal quantity of input to produce the profit-maximizing yield $f(\bar{x}^*, \ \bar{w})$. If 'bad' weather occurs (e.g. a heat wave), the production function moves downward, and yield is now represented by $f(x_1, \ w_1)$, i.e. the red line. Point B would now be the new optimum considering fertilizer input use as fixed.

The vertical distance between point A and B, that is $f(\bar{x}^*, \ \bar{w}) - f(\bar{x}^*, \ w_1)$, represents the agronomic impact of the weather shock. However, under these new weather conditions the farmer could modify the fertilizer use within the growing season in response to the change in actual weather and move it from $\bar{x}^*$ to x_1^*. After this adaptation in fertilizer use, yield increases up to point C. The vertical distance from B to C, that is $f(x_1^*, \ w_1) - f(\bar{x}^*, \ w_1)$, represents the adaptation impact. The difference between the agronomic effect and the adaptation effect leads to the total impact of the weather shock (vertical distance between A and C). The total impact is assumed to be captured by the reduced form estimation, but the great advantage of the structural model is given by the possibility to *quantify* also the agronomic and the adaptation impacts.

This approach is therefore well suited not only to assess the total impacts caused by shifting weather conditions on crop production, but also to understand if farmers adapt to these conditions on the intensive margin, i.e. adjusting input applications.

3. Empirical strategy

In the reduced form model, we define crop yield as a quadratic specification of temperatures and precipitation:

$$y_{i,t} = \beta_1 T_{i,t} + \beta_2 T_{i,t}^2 + \gamma_1 P_{i,t} + \gamma_2 P_{i,t}^2 + \alpha_i + \varepsilon_{i,t}, \tag{2}$$

where $y_{i,t}$ is the yield for farm i, in year t. T represents the average temperature during the crop-specific growing season and T^2 represents its squared term. P and P^2 represent the total precipitation during the growing season and its squared term, respectively. α_i represents farm fixed effects to account for time-invariant farm heterogeneity. Finally, $\varepsilon_{i,t}$ is an i.i.d. error term.

The literature analysing the yield-weather relationship considers the use of many non-linear functional specifications, like piecewise regressions using the concept of growing degree days, binned measures of temperature, or flexible splines (Ortiz-Bobea 2021). Moreover, the impact of weather variables could be considered during different phenological phases, since temperature has heterogeneous effects during distinct stages of plant growth. The choice of a quadratic functional form is driven by two considerations, which are related to the structural specification. First, using a specification with growing degree days would imply the choice of a crop-specific temperature threshold, which is justified by crop phenology but does not necessarily correctly identify the relationship between input productivity and temperature. Second, a quadratic functional form allows for the estimation of non-linear effects in a flexible manner while keeping the structural model parsimonious in terms of coefficients to be estimated. This same consideration applies to the use of a specification that defines weather variables according to phenological phases, since the increase in the number of covariates would pose significant challenges for convergence of the structural model. For completeness, in Supplementary materials S3 and S4, we discuss and provide results using alternative reduced-form model specifications.

In the structural model, crop production is defined by a production technology with two variable inputs.[2] We follow Bareille and Chakir (2024), and for each crop we assume a quadratic production function with two inputs (fertilizers and pesticides) like the following:

$$y_{i,t} = \alpha(w_{i,t}) - \frac{1}{2}\sum_{k=1}^{2}\sum_{l=1}^{2}\gamma_{k,l}^{-1}(w_{i,t})[\beta_k(w_{i,t}) - x_{i,k,t}][\beta_l(w_{i,t}) - x_{i,l,t}], \tag{3}$$

where $y_{i,t}$ is the yield for farm i in year t, $x_{i,k,t}$ denotes the quantity of the kth input, $\alpha(w_{i,t})$ is a production parameter, while $\beta_k(w_{i,t})$ and $\gamma_{k,l}^{-1}(w_{i,t})$ are sets of input-specific parameters where $\{k, l\} \in \{1, 2\}^2$. These parameters have agronomic interpretations: $\alpha(w_{i,t})$ is the maximum yield achievable under the given weather conditions, $\beta_k(w_{i,t})$ is the optimal amount of input k to be used in order to achieve the maximum yield and $\gamma_{k,l}^{-1}(w_{i,t})$ are technical shifters that are used to characterise the productivity of the inputs ($\{k, l\} \in \{1, 2\}^2$). This type of quadratic specification of the production function, implemented by Femenia and Letort (2016) based on a single input specification first proposed by Pope and Just (2003), is convenient since it allows technical changes in the production technology to translate directly into shifters of the input demand functions.[3]

The original feature introduced by Bareille and Chakir (2024) is the specification of these parameters as a function of weather ($w_{i,t}$), more precisely of a quadratic specification of temperature and precipitation:

$$\begin{aligned}
\alpha(w_{i,t}) &= \alpha^0 + \alpha^T T_{i,t} + \alpha^{T^2} T_{i,t}^2 + \alpha^P P_{i,t} + \alpha^{P^2} P_{i,t}^2, \\
\beta(w_{i,t}) &= \beta^0 + \beta^T T_{i,t} + \beta^{T^2} T_{i,t}^2 + \beta^P P_{i,t} + \beta^{P^2} P_{i,t}^2, \\
\gamma_{k,l}^{-1}(w_{i,t}) &= \gamma^0 + \gamma^T T_{i,t} + \gamma^{T^2} T_{i,t}^2 + \gamma^P P_{i,t} + \gamma^{P^2} P_{i,t}^2.
\end{aligned} \tag{4}$$

The farmer's profit maximization problem for the production technology described in equation 2, and assuming risk neutrality, can then be stated as:

$$\pi_{i,t} = \max_{x_{i,t}} \left\{ p_t^y y_{i,t} - p_t^{x\,\prime} x_{i,t} \mid y_{i,t} = f(x_{i,t}, w_{i,t}) \right\}, \tag{5}$$

where p_t^y and p_t^x are respectively the crop and input prices.

Solving the maximization problem, we obtain the input demands and the optimal yield for the considered crop. The resulting system of three equations can then be estimated using SUR (Seemingly Unrelated Regression):

$$\begin{cases}
y_{i,t} = \alpha(w_{i,t}) - \delta_{1,1}(w_{i,t}) \dfrac{(p_{1,t}^x)^2}{2(\mathbb{E}(p_t^y))^2} - \delta_{2,2}(w_{i,t}) \dfrac{(p_{2,t}^x)^2}{2(\mathbb{E}(p_t^y))^2} - \delta_{1,2}(w_{i,t}) \dfrac{(p_{1,t}^x p_{2,t}^x)^2}{2(\mathbb{E}(p_t^y))^2} + \omega_i^y + \mu_{i,t}^y \\
x_{i,1,t} = \beta_1(w_{i,t}) - \delta_{1,1}(w_{i,t}) \dfrac{p_{1,t}^x}{\mathbb{E}(p_t^y)} - \delta_{1,2}(w_{i,t}) \dfrac{p_{2,t}^x}{\mathbb{E}(p_t^y)} + \omega_{i,1}^x + \mu_{i,1,t}^x \\
x_{i,2,t} = \beta_2(w_{i,t}) - \delta_{2,2}(w_{i,t}) \dfrac{p_{2,t}^x}{\mathbb{E}(p_t^y)} - \delta_{1,2}(w_{i,t}) \dfrac{p_{1,t}^x}{\mathbb{E}(p_t^y)} + \omega_{i,2}^x + \mu_{i,2,t}^x
\end{cases}, \tag{6}$$

where $y_{i,t}$ denotes yield for farm i in year t. $x_{i,k,t}$ denotes the kth input (1 for fertilizers and 2 for pesticides) according to the subscript. $w_{i,t}$ represents the weather, in our setting temperature and precipitation. p_t^y and $p_{k,t}^x$ represent the crop price and the input prices, respectively. ω_i^y and $\omega_{i,k}^x$ represent the farm-specific fixed effects. $\mu_{i,t}^y$ and $\mu_{i,k,t}^x$ represent the remaining error terms. $\alpha(w_{i,t})$, $\beta_k(w_{i,t})$, and $\delta_{k,l}(w_{i,t})$ are the parameters to be estimated, where $\delta_{k,l}(w_{i,t})$ are functions of the technical shifters $\gamma_{k,l}^{-1}(w_{i,t})$.[4] As we indicated above, we assume the parameters to be defined by a quadratic specification of temperature and precipitation, hence allowing for the productivity of inputs to vary with weather conditions.

Through the proposed structural model and the estimated coefficients, it is then possible to quantify the input-use adaptation behaviour of farmers and to distinguish the adaptation effects of these adjustments from the direct agronomic effects of temperature increases on plant growth. We compute the temperature elasticities of input applications, i.e. how much fertilizer and pesticide use change in percentage points for a one per cent temperature increase at the sample median temperature, using the formula:

$$\varepsilon_{x_k}^T = \left(\hat{\beta}_k^T + 2\hat{\beta}_k^{T^2} \bar{T} - \frac{\bar{p}_k^x}{\bar{p}^y} \left(\hat{\gamma}_{k,k}^T + 2\hat{\gamma}_{k,k}^{T^2} \bar{T} \right) - \frac{\bar{p}_l^x}{\bar{p}^y} \left(\hat{\gamma}_{k,l}^T + 2\hat{\gamma}_{k,l}^{T^2} \bar{T} \right) \right). \tag{7}$$

The adaptation effect can then be computed as the productive impact of the input application adjustments described by the elasticity in equation (7) at the sample mean values. Specifically, we compute it as an elasticity using the formula:

$$\varepsilon^T_{ADy} = \varepsilon^T_{x_1}\left\{\gamma^{-1}_{1,1}(\bar{w})\left[\beta_1(\bar{w}) - \bar{x}_1\right] + \gamma^{-1}_{1,2}(\bar{w})\left[\beta_2(\bar{w}) - \bar{x}_2\right]\right\}$$
$$+ \varepsilon^T_{x_2}\left\{\gamma^{-1}_{2,2}(\bar{w})\left[\beta_2(\bar{w}) - \bar{x}_2\right] + \gamma^{-1}_{1,2}(\bar{w})\left[\beta_1(\bar{w}) - \bar{x}_1\right]\right\}. \quad (8)$$

4. Data

We use farm-level data from the *Rete di Informazione Contabile Agricola* (RICA) database, the Italian FADN provider, which offers accounting-based information on the value of production, cultivated crop area, and expenditures on fertilizers and pesticides for a representative sample of Italian farms from 2008 to 2022. Crucially for our estimation, RICA provides input expenses attributed at the crop level.[5] We consider the production of corn and common wheat, which are two of the most important cereal crops in Italy. For instance, in 2023, wheat (common and durum) accounted for 49 per cent of Italian cereal production, while maize represented 38 per cent (ISTAT 2023).

Given the use of a fixed effect approach, we restrict the sample to farmers who are included in the panel for at least 3 years. The final sample consists of 682 corn producers (4,463 observations), and 1,141 common wheat producers (6,472 observations). While this kind of farm-level data allows for analysis at a finer spatial scale, it has some limitations. For instance, RICA collects the monetary value of production from farmers and the quantity produced is then extrapolated from it. An additional concern could be given by the fact that input data is also provided as monetary expenses per crop during the fiscal year, rather than the actual quantities used.

While this might introduce measurement error, it has been demonstrated that input expenses are indeed highly correlated to actual use and, at least regarding pesticides, farmers exhibit limited year-to-year storing behaviour (Bareille et al. 2024). Yield, fertilizer applications, and pesticide applications were winsorized at the 1st and 99th percentiles to correct implausible extreme values. Prices of inputs and outputs are obtained from ISTAT at the national level (ISTAT 2023). Figure 3 shows the geographical distribution of the considered farms in the Italian territory.

Concerning weather data, hourly temperatures are obtained from ERA5-Land (Muñoz Sabater 2019), adjusted using high-resolution climatology data and matched with farm data at the municipality level. Specifically, given the relatively coarse spatial resolution of the ERA5-Land database (9×9 km), we refine temperature values using high-resolution climatology data (1991–2020 monthly normals, i.e. mean monthly values over the period) developed by Brunetti et al. (2014), with a spatial resolution of 0.9 km by 0.9 km. The spatial distribution of temperature normals is tightly related to the physiographical features of the Earth's surface, while the anomalies (deviations from the normal) are more homogeneous in space. We compute hourly anomalies using ERA5-Land data (i.e. the deviation of the hourly temperature from the 1991–2020 monthly mean computed from the same source) and then add them to the corresponding raster of monthly climatologies in order to obtain a final temperature dataset which is extremely granular on both a spatial and time dimension. Section S1 in the Supplementary materials provides a visual comparison of the spatial resolution of the two sources. In this way, we are able to obtain a high spatial and temporal detail and reduce interpolation errors when matching farms to the temperature grid points. Hourly data for precipitation is also obtained from ERA5-Land and then matched to the farm municipality. From the hourly data we then compute the growing season mean temperatures and total precipitation according to the considered crop.

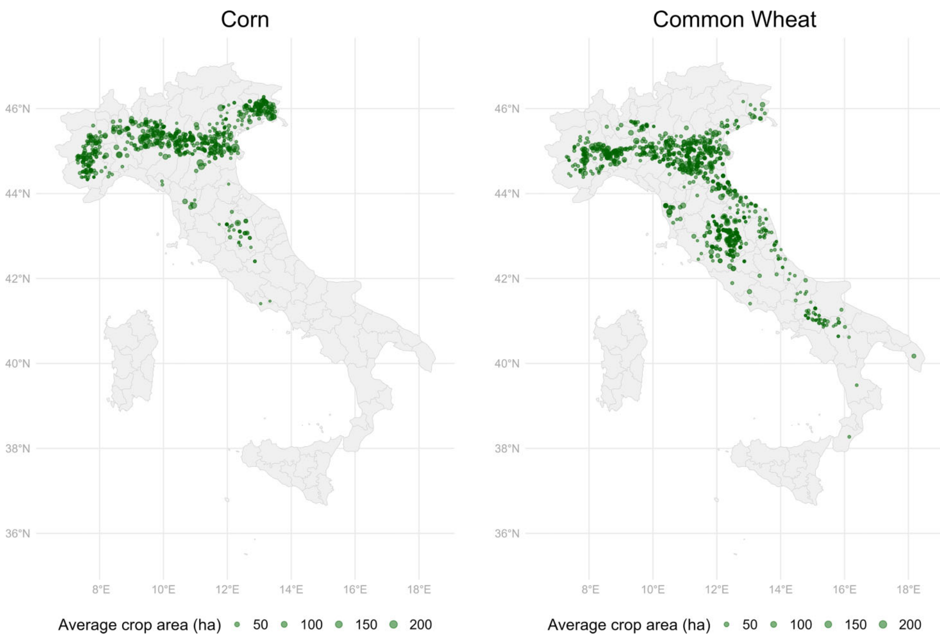

Figure 3 Location of the farms' municipalities included in the samples.

Considering typical sowing and harvest dates in Italy, for corn the growing season starts in March and ends in September, while for common wheat it covers the October-July period.

The climate change temperature projections used in the analysis are obtained from the dataset SD-EQM_GCMs_IT (Statistical Downscaling through Empirical Quantile Mapping for an ensemble of Global Climate Models over ITaly) (Fedele et al. 2025), which provides high-resolution (∼5.5 km) climate information specifically tailored to Italy. The dataset consists of statistically downscaled data derived from an ensemble of CMIP6 Global Circulation Models (GCMs) forced by scenarios SSP1-2.6 and SSP3-7.0. We use projections from four GCMs (CESM2, CMCC-CM2-SR5, CNRM-ESM2-1, EC-Earth3-Veg) under the SSP3-7.0[6] in order to construct ensemble projections (correcting for differences in baseline years with ERA-5 Land data). Table 1 provides the summary statistics of the variables included in the analysis.

5. Results

Table 2 reports the results of the reduced-form model outlined in equation 1 for corn and wheat, using different adjustment procedures to compute the standard errors. We find that both crops display a concave relationship with temperature and that corn production is more sensitive to temperature than wheat, a result that is consistent with the literature on both crops (Schlenker and Roberts 2009; Burke and Emerick 2016; Mérel and Gammans 2021). Moreover, both crops do not seem to be particularly affected by total levels of precipitation. The precipitation coefficients for corn are not significant, while for wheat the coefficient of the linear term is negative and significant, although small in magnitude. Since corn in Italy is an irrigated crop, we would expect a similar result. Wheat instead is mostly rainfed and hence we would have expected a concave relationship (as found by Chavas et al. 2019), where very dry or very wet growing seasons have a negative effect on yields. A possible explanation is that the observed data fall primarily along

Table 1 Summary statistics.

	Corn				Common wheat			
Variable	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Average temperature (°C)	18.95	1.04	12.49	21.06	12.96	1.09	8.88	17.38
Total precipitation (mm)	716.50	199.57	252.14	1453.41	828.83	216.63	401.10	1842.53
Yield (100 kg/ha)	110.19	24.10	41.67	165.32	56.04	12.82	22.77	85.00
Area (ha)	19.90	28.66	0.04	403.81	17.34	25.12	0.15	345.23
Output price (2010 = 100)	115.5	26.84	77.74	204.25	117.69	25.85	81.89	195.27
Fertilizer price (2010 = 1)	1.02	0.20	0.85	1.83	1.03	0.23	0.85	1.83
Pesticide price (2010 = 1)	1.01	0.10	0.87	1.25	1.03	0.11	0.87	1.25
Fertilizer applications (€/ha, deflated to 2010)	258.92	148.14	15.20	946.00	144.39	86.85	8.91	608.63
Pesticide applications (€/ha, deflated to 2010)	126.81	77.82	9.38	517.72	88.34	60.66	5.59	369.05

Table 2 Reduced-form estimates of the yield-weather relationship.

	Coefficient	**Robust SE**	**Clustered SE**	**Conley SE**
		Corn		
Mean temperature	42.225	11.111***	15.775***	24.260*
Mean temperature squared	−1.135	0.293***	0.420***	0.651*
Total precipitation	−0.002	0.012	0.015	0.013
Total precipitation squared	5.38×10^{-6}	7.47×10^{-6}	9.43×10^{-6}	9.96×10^{-6}
		Common Wheat		
Mean temperature	7.007	3.340**	4.182*	4.072*
Mean temperature squared	−0.271	0.123**	0.162*	0.166
Total precipitation	−0.011	0.004***	0.006*	0.004***
Total precipitation squared	3.57×10^{-4}	2.15×10^{-4}*	3.09×10^{-4}	2.28×10^{-4}

Notes: Clustered SE are clustered at the Agrarian Region (Agrarian Regions (Regioni Agrarie) are territorial subdivisions defined by ISTAT used for agricultural and land classification. Each region shares similar agricultural practices, climate conditions, and terrain. The Italian territory is divided in about 300 agricultural regions.) - year level. Conley SE are computed with a distance cutoff of 100 km (A 100 km cutoff should allow to capture the spatial decay of error correlation, considering the size of administrative units (provinces) or agro-ecological regions. Section S2 in the supplementary materials provides a sensitivity analysis by varying the Conley distance cutoffs. The results remain significant for more expansive windows of 200 km and 300 km and, for corn, for a smaller threshold of 50 km.). *, ** and ***indicate p-values lower than 0.1, 0.05 and 0.01, respectively.

the descending section of the yield response function, where precipitation levels are already sufficient or excessive. Sections S3 and S4 in the Supplementary materials display the reduced form results for, respectively, a model specification that considers weather realizations in different phenological phases and a model specification with cumulative temperature (i.e. beneficial and harmful degree days). The results of both models are consistent with the results presented in Table 2.

To compare the results of the reduced-form and structural models, we compute yield-temperature elasticities of both models at different quantiles of the growing season

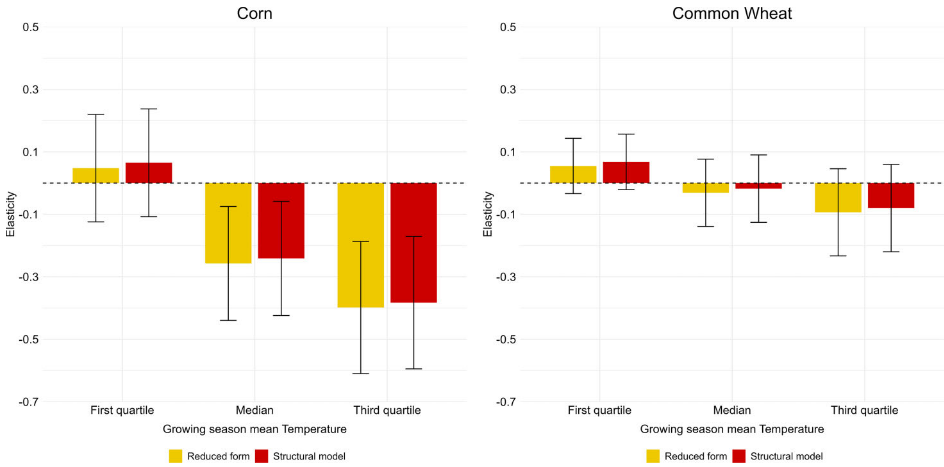

Figure 4 Yield-temperature elasticities at different temperature quantiles. *Notes:* For corn, the quantiles (25th, median and 75th) correspond respectively to 18.47°C, 19.25°C, and 19.59°C. For wheat 12.48°C, 13.18°C and 13.64°C. A 1 per cent increase in temperature at the median corresponds to + 0.19°C for corn and + 0.13°C for wheat. Vertical bars indicate the 90 per cent confidence intervals.

temperature distribution. The elasticities for the structural model are computed starting from the estimated coefficients[7] (reported in Section S5 in the Supplementary materials) and the standard errors are computed using the delta method. Figure 4 plots the elasticities for both crops and shows that the reduced-form and the structural model indicate comparable effects, supporting the hypothesis that reduced-form models already capture in-season adaptation. As expected by the coefficients estimated in the reduced-form model, we find that there is no significantly negative effect on Italian wheat yields, even at higher percentiles of the temperature distribution, while there is a positive elasticity (non-significant) at lower temperatures. For corn instead there is a negative and significant effect already at the median temperature. A 1 per cent increase in temperature at the median (i.e. a 0.19°C increase) reduces corn yields by approximately 0.25 per cent. The results for both crops are in line with the literature. For instance, Bareille and Chakir (2024) find a positive elasticity (0.57) of wheat yields at the sample mean temperature (in a colder region). Studies of corn yields in other countries instead suggest significant damage from increased temperatures (e.g. Schlenker and Roberts 2009; Mérel and Gammans 2021). As a robustness check, section S6 in the Supplementary materials presents a structural specification with cumulative temperatures (beneficial and harmful degree days) and compares the yield-harmful degree day elasticity of the model with the one obtained from the results of the reduced form model presented in Section 4 of the Supplementary materials. As discussed in Section 3, we advise a cautious interpretation of these results, as the temperature thresholds defining beneficial and harmful heat accumulation for crop growth do not necessarily apply to input productivity.

We then use the estimates of the structural model to investigate the behaviour of the farmers regarding input use, and to assess if they are indeed adapting the input choices to observed weather conditions. Table 3 displays the elasticity of fertilizer and pesticide use to temperature,[8] computed at different quantiles of the temperature distribution based on Equation (7). The estimated elasticities depict a heterogeneous setting. For corn, farmers in the lower part of the temperature distribution increase the use of fertilizer quite substantially in response to marginal temperature increases, whereas this effect diminishes at higher temperatures. In

Table 3 Input-temperature elasticities.

	First quantile	Median	Third quantile
		Corn	
Fertilizers	0.994*** (0.307)	0.692** (0.298)	0.360 (0.400)
Pesticides	0.701* (0.366)	0.945*** (0.352)	1.209*** (0.464)
		Common wheat	
Fertilizers	0.258 (0.19)	0.478** (0.213)	0.674** (0.299)
Pesticides	0.494** (0.209)	−0.055 (0.227)	−0.548* (0.316)

Notes: For corn, the quantiles (25^{th}, median and 75^{th}) correspond respectively to 18.47°C, 19.25°C, and 19.59°C. For wheat 12.48°C, 13.18°C and 13.64°C. A 1 per cent increase in temperature at the median corresponds to + 0.19°C for corn and + 0.13°C for wheat. In brackets the standard errors obtained with the delta method. *, ** and *** indicate p-values lower than 0.1, 0.05 and 0.01, respectively.

Table 4 Temperature elasticities: agronomic and adaptation effects.

	First quantile	Median	Third quantile
		Corn	
Total	0.065 (0.105)	−0.241** (0.111)	−0.383*** (0.129)
Agronomic effects	−0.011 (0.105)	−0.272*** (0.111)	−0.402*** (0.129)
Adaptation effects	0.076*** (0.009)	0.031*** (0.007)	0.02*** (0.007)
		Common Wheat	
Total	0.068 (0.054)	−0.018 (0.066)	−0.08 (0.085)
Agronomic effects	0.059 (0.054)	−0.04 (0.066)	−0.124 (0.085)
Adaptation effects	0.009** (0.004)	0.022*** (0.005)	0.044*** (0.008)

Notes: For corn, the quantiles (25^{th}, median and 75^{th}) correspond respectively to 18.47°C, 19.25°C, and 19.59°C. For wheat 12.48°C, 13.18°C and 13.64°C. A 1 per cent increase in temperature at the median corresponds to + 0.19°C for corn and + 0.13°C for wheat. In brackets the standard errors obtained with the delta method. *, ** and *** indicate p-values lower than 0.1, 0.05 and 0.01, respectively.

contrast, pesticide use displays the opposite pattern, with the estimated elasticity rising at higher temperatures. Regarding wheat, fertilizers' elasticity is increasing with temperature, while for pesticides, instead it decreases and becomes negative for higher quantiles of the distribution (i.e. farmers reduce the quantity of pesticides applied in response to temperature increases).

It is possible to assess the consequences of this adaptation behaviour on crop yields, disentangling the agronomic and adaptation effects, as illustrated in Fig. 1 and following Equation (8). The adaptation effect is given by the productive impacts of the changes in input applications. The agronomic effect is then computed as the difference between the total effect and the adaptation effect. Table 4 shows results for corn and wheat, respectively. We observe a strong adaptation effect for corn, which is reducing the negative impact of agronomic effects by 11 per cent at the median temperature (i.e. $0.031/|-0.272|$).

The adaptation effect is, however, decreasing at higher temperatures (5 per cent in the third quantile), suggesting less potential for adaptation to further (non-marginal) increases in

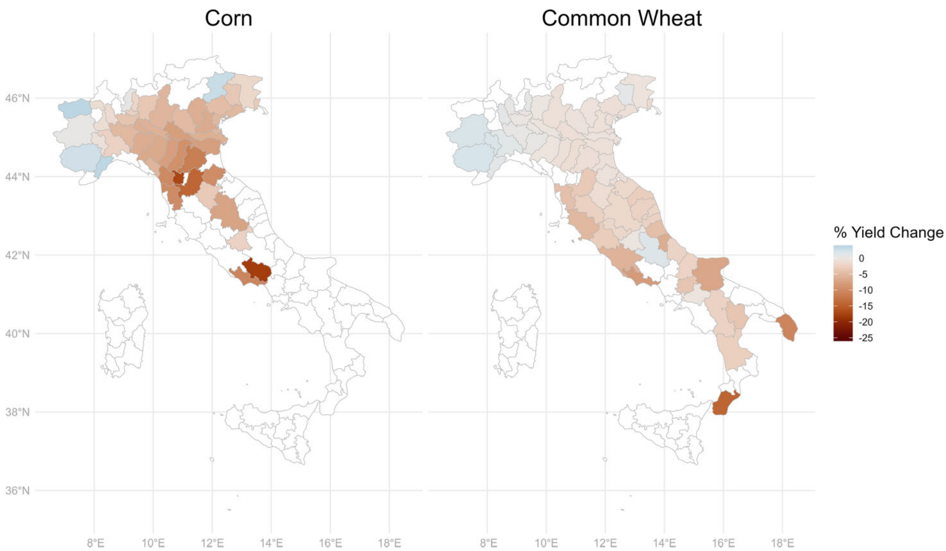

Figure 5 Projected percentage change in yields in 2050 (SSP3-7.0 scenario). *Notes:* Province (NUTS3) level estimates of the impact of temperature changes on crop yields in 2050 (2035–2065) (per cent change) under SSP3-7.0. The projections are based on the results reported in Section S7 in the Supplementary materials, obtained using the structural model.

temperature. Interestingly, the adaptation effect is higher at lower temperatures, indicating that farmers in colder areas are able to take advantage of warmer-than-average seasons by adjusting their input use. Regarding wheat, the agronomic effects are overall more modest in absolute terms, as displayed in Fig. 4. Even if modest, adaptation effects are significant, showing gains from input adjustments.

As an illustrative non-marginal impact assessment, Fig. 5 displays the projected percentage change in yields at the province level in 2050, under SSP3-7.0 for the model ensemble using the structural estimates (see Section S5 in the Supplementary materials), under the assumption that crop-specific cultivated areas do not change in the considered future scenarios. Nonetheless, it allows us to characterise province heterogeneity in climate change projections. Across the provinces considered in our analysis, growing season mean temperatures increase on average by 2.10°C for corn and by 1.86°C for wheat. Corn production is more severely affected, and the worst impacts are found in central Italy and in the lower Po valley, with some provinces showing up to a 18 per cent decrease in yields. For wheat, the impacts are overall more modest if compared to corn, but some provinces located in the southern part of the country suffer significant damages (up to 14 per cent). Provinces with higher elevation and cooler climates show modest yield gains for both crops. Aggregating the production of the provinces included in this analysis and considering provincial production shares in the 2010–2020 period, our estimates suggest that production at the national level could decline by 4.42 per cent for corn and 0.72 per cent for wheat. In Section S8 in the Supplementary materials, we display projection maps for the individual models, in order to account for inter-model heterogeneity.

As shown in Section S7 in the Supplementary materials, under the projected scenario, the adaptation effects are small (for example, for corn, they would reduce agronomic damages by approximately 5 per cent on average) and not significant for both crops in all provinces. This result suggests that adaptation through growing season input adjustments is more effective for marginal changes in temperature, but its potential in offsetting the damages of non-marginal temperature increases is limited. These results should be interpreted with caution and as indicative, as they involve temperature ranges that extend beyond the historical experience of many provinces and do not account for technological innovation and adaptation on other margins.

6. Conclusions

The paper makes a contribution to our understanding of the temperature-yield relationship and the related farmers' input adaptation behaviour within the growing season, focusing on corn and wheat yields, two of the most important crops cultivated in Italy. More specifically, we are able to assess the short-run adaptation behaviour of farmers in response to weather conditions, with regard to adjustments in fertilizers and pesticides. We provide external validity to the structural model developed by Bareille and Chakir (2024), using data from a different area and a larger dataset, for a new country and a new crop, corn, with a different photosynthetic process (C4) and growing season.

Our findings highlight that, in accordance with results obtained in other countries, both crops show a concave relationship with growing season mean temperatures. Corn displays a higher sensitivity to temperature increases than wheat. The marginal effect of temperature on corn yields is negative and statistically significant already at the sample median temperature. There is, however, evidence of input adaptation for corn, which effectively mitigates a significant part (11 per cent at the median temperature) of the agronomic impacts on plant growth. As we stated in the introduction, these results are quite relevant since, to our knowledge, there is currently no study that assessed farmers' adaptation using structural models and observational farm-level data for corn. Regarding wheat, we find that its sensitivity to temperature increases is indeed smaller, as we find no significant negative effect in our sample up to the third quantile of the temperature distribution. This result is consistent with the ones obtained by Bareille and Chakir (2024), since they find a positive effect of temperature on yields for wheat in a region (Meuse, north of France) with a more temperate climate. Even though we do not observe extensive impacts, there is evidence of a moderate adaptation effect on wheat yields from input adjustments in response to temperature.

Illustrative simulations of the agronomic and adaptation effect under the SSP3-7.0 scenario in 2050 show significant damages for corn in the majority of provinces, while the effect is of smaller magnitude and mostly never significant for wheat. Aggregating over all the provinces considered in the analysis, corn yields are projected to decrease by 4.42 per cent and wheat yields by 0.72 per cent. For both crops, the input adaptation effect under the 2050 climate projections is limited and never significant. This result suggests that adaptation through input use can be an effective strategy to offset some of the impacts of marginal temperature increases. However, it does not seem to be effective as a long-term adaptation strategy to non-marginal temperature increases, highlighting the need for the adoption of other adaptation strategies, like changing crop varieties, adjusting planting or sowing dates or cropland allocation, especially for corn.

We acknowledge that the results should be interpreted with caution due to some limitations. The analysis is based on an unbalanced panel, and measurement error in the variables likely contributes to the relatively wide confidence intervals. In addition, we are only able to identify short-term adaptation through input use, hence the findings should be considered as not accounting for long-term dynamics of the agricultural sector or for other adaptation strategies (i.e. irrigation).

Nonetheless, we believe these results provide valuable insights to inform agricultural and environmental policy at the national and European level, in light of the current input reduction targets. By characterizing agricultural inputs as a short-term adaptation mechanism, our study highlights the trade-offs faced by farmers and policymakers to reconcile economic resilience with environmental sustainability. While reducing input use is essential for preserving biodiversity and long-term environmental health, these targets must be balanced against productive stability (Gohin 2024), since inputs can provide an adaptation strategy to adverse weather conditions.

End notes

1 In 2023 corn harvest reached 5.331 million tonnes over a cultivated area of 498,500 hectares, while common wheat production totalled 3.688 million tonnes over a cultivated area of 1,269,000 hectares (CREA 2024).

2 The choice of fertilizers and pesticides as the variable inputs is justified since these are arguably the two main inputs employed by farmers during the growing season, i.e. when crop allocation has already been decided. For corn also another adaptation strategy, irrigation, is available to farmers, but due to data limitations the actual amount of water used is not available. This means that our estimates can be interpreted as a lower bound of the adaptation effect for corn. Since common wheat is rainfed in Italy, the above consideration is not extended to this crop.

3 We refer the reader to Bareille and Chakir (2024) and Femenia and Letort (2016) for an extended discussion of the structure and interpretation of the parameters.

4 Specifically, $\delta_{k,l}(w_{i,t}) = \frac{\gamma_{k,l}^{-1}(w_{i,t})}{\gamma_{1,1}^{-1}(w_{i,t})\,\gamma_{2,2}^{-1}(w_{i,t}) - \gamma_{1,2}^{-2}(w_{i,t})} \quad \forall\{k; l\} \in \{1; 2\}$.

5 Notice that this level of disaggregation is a unique feature of the RICA dataset, since the EU FADN only provides input use data aggregated at the farm level.

6 We do not include scenario SSP1-2.6 since it displays very limited changes in temperature compared to current levels.

7 Importantly, the estimated parameters of the production function respect the assumption of nondecreasing and concave relationship with the two inputs, fertilizers and pesticides.

8 We focus on elasticities with respect to temperature since it is our main variable of interest, but elasticities can be computed also with respect to precipitation starting from the structural estimates.

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Supplementary material

Supplementary material are available at *Q Open* online.

Conflicts of interest

The authors declare no conflicts of interest.

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Data availability

The authors do not have permission to share the RICA database farm data used in this study. Climate data are available from the corresponding author upon request. The code used to perform the analysis is available at https://github.com/giacomocou/RICA-input-adaptation.

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