Weathering the Change: Modeling Crop Choices in Response to Climate Variability

1.1 Introduction

As weather patterns become more variable under climate change, the suitability of crops traditionally grown in specific regions may shift (Anh Hoang et al., 2022; Heikonen, et al., 2025). As crop-specific heat and moisture requirements vary, climate change will impact crops differently. Water-intensive crops may no longer thrive in regions experiencing drier conditions, whereas heat and drought-tolerant varieties may become more viable. The change in weather patterns will potentially alter crops' comparative advantages. Under such circumstances, sticking to traditional cropping patterns can lead to substantial losses as lower productivity will translate into lower profits. To mitigate these losses, farmers are likely to switch to crops better suited to the changing climate (Rising & Devineni, 2020; Sloat, et al., 2020), which may lead to significant market and welfare implications.

The role of climate change in driving land-use changes and producer adaptation strategies is a relatively understudied topic. Recent studies have investigated farmers' adaptations to climate change, but most have been conducted at an aggregated (i.e. county or state) (Rising & Devineni, 2020; Mu et al., 2017) or very localized scale (Moniruzzaman, 2015; Ahmed et al., 2023). One major challenge in quantifying farmers' adaptation, particularly through crop choices, is the scarcity of field-level data. Crop choices or adaptation decisions are made at the field-level by farmers, but such data is often unavailable (Mccarl et al., 2014). Studies relying on county- or state-level data fail to capture the granularity of decision-making and localized studies based on surveys of a small number of farmers may not be able to capture the heterogeneity of cropping decisions across different regions and conditions.

Another challenge in credibly identifying farmers' adaptations to climate change is the complex interaction between weather patterns and market conditions. Weather and field productivity influence crop yields and, ultimately, profits. Farmers base crop choices on expected profits, yet many studies inaccurately assume constant profitability under climate scenarios (Moniruzzaman, 2015; Cui, 2020). Some studies incorporate impact of changing profitability under climate change on crop choices using two-step modeling approaches which first simulate future yields and profits and, then predict optimal crop choices based on these simulated profits (Arora et al., 2019; Rising & Devineni, 2020). However, because of a lack of data on field-level profits, these studies use aggregated measures such as county or state-level profits or prices, which introduce measurement error and may underestimate the impact of profitability on crop choices.

In this paper, we rigorously investigate the factors that determine farmers' cropping decisions and how exogenous shocks, specifically climate and market conditions, affect crop choices. Our approach consists of two key steps. First, we estimate crop-specific yield-weather models for five crops including maize, soybean, sunflower, wheat, and rapeseed using field-level yield data. We regress crop-specific yields on 3°C temperature bins representing hours of exposure and soil moisture during different growth stages using two-way fixed effects estimation. The goals of the yield-weather model are twofold; to provide us with crop-specific thresholds of extreme weather and to allow us to predict how yields change under climate change. We then identify the key variables influencing farmers' cropping decisions by integrating the yield model results into a panel conditional logit crop choice model that utilizes field-level data on farmers' crop choices. The model provides us a framework to simulate how choices adjust under climate change. We incorporate climate change impact on yields via our profit variables to incorporate how shifts in net crop returns influence predicted crop choices. This modeling approach allows us to quantify the welfare implications of crop switching in response to changing climatic and economic conditions.

Our paper aims to address some of the issues prevalent in the current literature. Overall, this paper has three major contributions. First, we develop an innovative crop choice model that effectively integrates climatic, hydrological, and economic factors to precisely capture the decision-making processes of farmers. Crop choices depend on several factors that are too often ignored in the traditional crop choice models, including variables such as yield-specific profit and field-level irrigation status that are either excluded or proxied by other variables in the past literature (Seo & Mendelsohn, 2008). By including these variables, we characterize a crop choice model that is more closely aligned with farmers' decision-making processes in the real world. Additionally, we include both short and long-term weather in our crop choice model. Previous literature has often only included short-term weather fluctuations, as recent weather events are more likely to shape farmers' crop choices (Ahmed et al., 2023; Seo & Mendelsohn, 2008). We believe that while recent weather events affect crop choices in an obvious manner, farmers often base their expectations of weather based on long-term climatic trends.

Second, the integration of findings from yield-weather models into the crop choice model is a relatively new approach. Incorporating yield results within our profit estimates in the crop choice model improves the measurement of profit's impact on crop choices. Additionally, re-estimating yields under climate change allows us to capture the intricate relationships between productivity, crop profits and crop choices that are often overlooked in the literature.

Third, having field-level data on crop yields and crop choices spread across an entire country is a significant improvement over the previous literature that has been conducted at an aggregated county-level. Our analysis is one of the few high-resolution studies providing us with significant heterogeneity across farmers' decisions and field characteristics that is often lost in aggregation.

Finally, we express these welfare effects of crop switching in monetary terms to provide a tangible measure of the economic costs and benefits of adaptation. In addition, we compare these outcomes to a no-switching counterfactual—where farmers are constrained to maintain their baseline crop choices— to quantify how much of the welfare loss from climate change is mitigated through adaptive behavior. This comparison highlights the economic value of adaptation and identifies the residual welfare losses that may justify targeted policy interventions to support farmers in managing climate risks.

The results from our yield-weather models reveal crop-specific thresholds for all five crops considered in our analysis. Using heat and cold thresholds for all spring crops including maize, soybean and sunflower, we find the heat-stress threshold to be 34°C and cold-stress threshold to be 4°C for spring crops. For winter wheat and rapeseed, we find an extreme heat threshold of 28°C and an extreme cold threshold of -5°C. Our simulations also indicate that yields change significantly under the future climate scenarios with projected decline of 8% for maize from 2040-2070 and increase of 2-3% for soybean, wheat and sunflower.

Next, we estimate a crop choice model using a panel conditional logit structure to determine the factors that play a significant role in driving farmers' crop choices. We find extreme weather events to reduce the likelihood of planting field crops as farmers prefer to leave land fallow. Long-term climatic averages play an important role in shaping crop choice decisions for instance, wetter conditions reduce the likelihood of leaving land fallow.

Results from our crop choice simulations indicate that farmers are likely to adjust their cropping patterns in response to evolving climatic and market conditions. Under the climate-change-only scenario, farmers are predicted to move away from soybean and rapeseed and shift towards wheat, sunflower, and maize. After accounting for changing market conditions, the share of maize declines, while wheat and sunflower shares increase. This crop switching, while adaptive, is associated with an average welfare reduction of 26,027 dinars per farmer—representing a 35% decline in profits.

This paper proceeds as follows. Section 1.2 provides a background of the study area. Section 1.3 describes the theoretical and empirical framework behind the yield-weather and crop choice model. Section 1.4 outlines the data used, and Section 1.5 presents the results from the yield-weather model, crop choice model, the simulations, and the welfare implications. Section 1.6 concludes and provides policy implications.

1.2 Study Area

Agriculture is at the heart of Serbian economy. The sector accounts for 12% of the GDP and employs approximately 21% of the labor force (International Trade Administration, 2022). Agriculture is mostly prevalent in the Vojvodina region. Commonly planted crops in the region include maize, soybean, sugar beet, sunflower, rapeseed, and wheat. These crops make up a significant share of Serbia's agricultural exports especially to the European Union and the US generating revenues of approximately $5.3 billion in 2016.

Source: (Allcock, Poulsen, & Lampe, 2024)

Over the last two decades, however, Serbia's agricultural sector has suffered tremendous losses due to climate change. An increase in the frequency of extreme weather events, including droughts, floods, and frost has hurt crop yields and agricultural production (FAO, 2023). In 2022 alone, the persistent drought lasting over 4 months reduced crop yields by 20-30%, incurring economic losses reaching a billion dollars (USDA, 2022).

Given the high risks that farmers are facing, there might be measures employed by farmers to mitigate the impacts of climate change. Farmers might have adapted their crop choices to reflect the changing weather conditions. However, little research has been done to understand the impacts that this crop switching can have on farmers' welfare and overall economic output of the agricultural sector. Research evaluating climate change impacts has traditionally focused on a single crop or a smaller study region. This paper investigates how farmers' crop choices adjust under climate change utilizing field-level data across all of Serbia and includes the six major field crops planted across Serbia. Estimating the welfare implications of these adaptations offers valuable insights into the agricultural sector's future potential and can inform effective climate change policy in Serbia.

1.3 Conceptual Framework

Extreme temperatures and erratic rainfall patterns affect yields for all crops. However, the impact varies across crops depending on their comparative advantage. Adjusting crop choices allows producers to partially mitigate the negative consequences of climate change. Our crop choice model allows us to identify the key variables that determine farmers' crop choices. Through our crop choice model, we determine the role that short and long-term weather play in shaping farmers' cropping decisions. Moreover, we estimate how market conditions that shape farmers' expectations of profitability impact crop choices. The conceptual framework is provided in Figure 1.

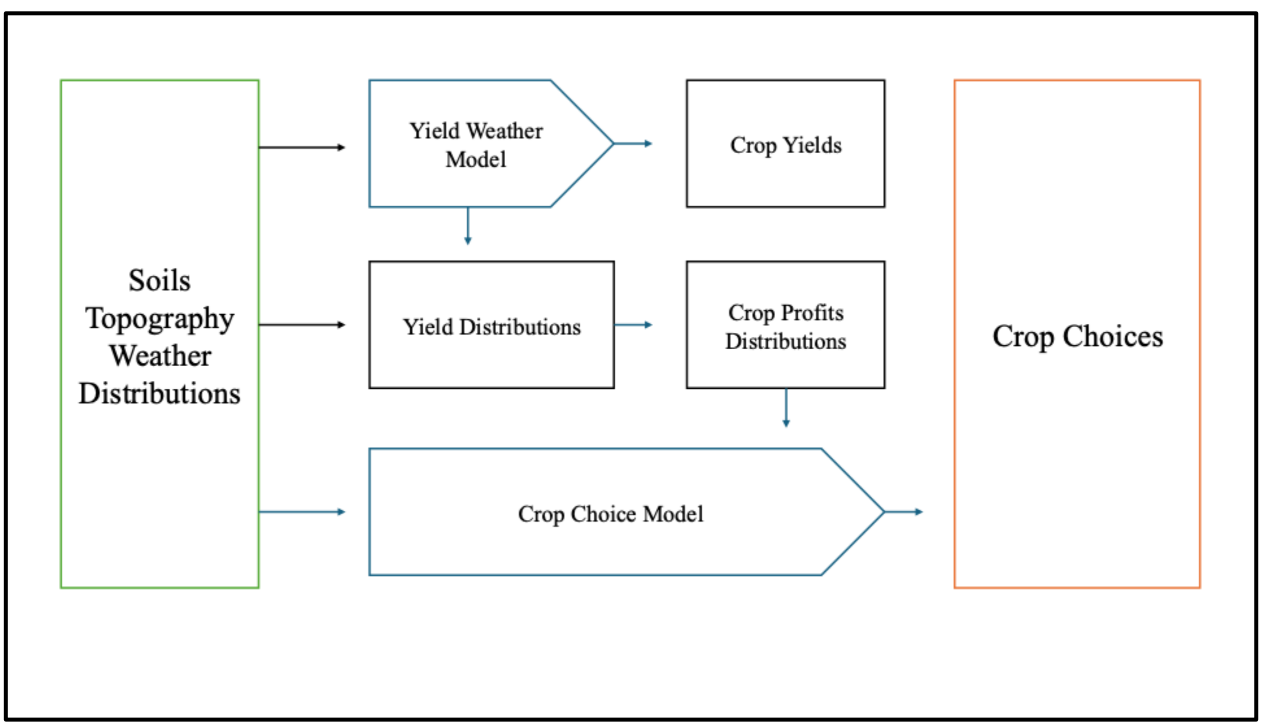

Figure 1. Conceptual Framework used in capturing climate change impact of crop choices. This figure is motivated by the conceptual framework employed in Arora et.al. (2019). However, it differs from their

framework as we employ a yield model to derive profit measures – net returns from crops - and include those in a crop choice model.

In our first step, using a fixed effects panel estimation we estimate the following yield weather model with detrended crop-specific yields, Y_{it}^{dt}, for field i and year t ranging from 2017-2022 as dependent variables:

$$\ln\left(Y_{it}^{dt}\right) = \beta_0 + \sum_k \beta_k TempExposureBin_{k,it} + \gamma_1 EarlySeasonSoilMoisture_{it} + \gamma_2 GrowingSoilMoisture_{it} + \gamma_3 HarvestingSoilMoisture + \mu_i + \varepsilon_{it} \quad (1)$$

Equation (1) is estimated separately for each crop – maize, soybean, sunflower, rapeseed, and wheat where the weather variables are for the growing season. The growing season for spring crops (maize, soybean, and sunflower) is April to September (Kresovic et al., 2014) and for winter wheat and rapeseed is October to June (Rancic et al., 2017). Double cropping is highly uncommon in the Serbian context (Marković et al., 2022). $TempExposureBin_{k,it}$ represents the total hours field i in year t is exposed to temperatures within the k-th temperature bin during the growing season. The exposure bins are constructed by interpolating temperatures at 15-minute intervals throughout each day using a sine function approximation between daily minimum and maximum temperatures, following the methodology adopted by Bobea et. al. (2019). Soil moisture during the growing season is divided into distinct stages reflecting crop development periods. For spring crops, early season soil moisture covers April to May, the main growing season spans June to August, and harvesting season corresponds to September (Pandžić et al., 2020). For winter crops, early season moisture includes October to February[1], the main growing season extends from March to May, and harvesting occurs in June (Jeločnik et al., 2019). These stage-specific soil moisture averages are used to capture differential impacts of soil moisture conditions throughout the crop growth cycle. Field fixed effects control for field characteristics that may impact yields, and standard errors are clustered at the more aggregated village-level.

We detrend yields to remove the steady, long-term increase attributable to technological improvements, policy changes, and other factors. Given the short length of our panel, including a year trend fails to accurately capture these long-term improvements in yields. Therefore, we use an external national yield trend estimated from data spanning 2006–2023 (FAO, 2025) and apply it uniformly across all crops. Although crop-specific trends may exist, due to data limitations we assume that broad technological improvements or policy changes affect all crops similarly. This approach allows us to isolate variations in crop yields that are solely attributable to weather changes.

Our yield weather regressions allow us to disaggregate temperature bins into beneficial and harmful temperatures for crop yields. It also allows us to more accurately estimate profits, which are particularly salient to producers. By quantifying the role that weather and market conditions play in determining crop choices, we can simulate how the choices adjust under plausibly

[1] Wheat enters dormancy when temperatures approach 0–5°C (Johnson et al., 2009). During this phase, crop development is essentially paused, and water requirements are minimal. For this reason, we classify soil moisture during the dormancy period as part of "early season soil moisture.

exogenous shocks to these factors. A stylized model that embodies the decision-making process of a representative farmers is presented below.

For each parcel *i*, a grower chooses a crop type *k* in year *t*. We assume the grower is profit-maximizing and each parcel produces a single crop during a growing season (fallow ground, maize, wheat, soybean, sunflower, and rapeseed). Expectations of this year's profit for the given crop k depend on past profits, $\Pi_{k,t-1}$, previous growing season's weather variables, $\mathbf{W}_{i,t-1}$, long-term moving climatic averages, $\mathbf{V}_{i,t-m:t-1}$, and other field-specific attributes, $\mathbf{X}_i$.

Under these assumptions, a grower will choose to plant the crop on parcel, *i*, that yields the maximum profit. The outside option is k =0, leaving the land fallow and its profits are normalized to 0. The grower's choice problem can be defined as

$$\Pi_{it} = \max_k \left(\Pi_1^*(\Pi_{1,t-1}, W_{i,t-1}, V_{i,t-m:t-1}, X_i), \dots \Pi_K^*(\Pi_{K,t-1}, W_{i,t-1}, V_{i,t-m:t-1}, X_i)\right) \quad k = 0,1, \dots, K \quad (2)$$

The probability of choosing crop k at time t to plant on parcel i is then represented as

$$\rho_{ikt} = Prob\left[\Pi_k^*(\Pi_{k,t-1}, W_{i,t-1}, V_{i,t-m:t-1}, X_i) > \Pi_j^*(\Pi_{j,t-1}, W_{i,t-1}, V_{i,t-m:t-1}, X_i)\right] \forall j \neq k \quad (3)$$

where ρ_{ikt} equals 1 if crop k is planted on parcel 1 at time t and 0 if any other crop is chosen.

Current period profits can be estimated as

$$\pi_{k,it} = \alpha\pi_{k,it-1} + \beta_k \boldsymbol{W'}_{i,t-1} + \eta_k \boldsymbol{V'}_{i,t-m:t-1} + \omega_k \boldsymbol{X'}_i + \theta_k Year + \tau_k + \varepsilon_{k,it} \quad (4)$$

where α represents impact of previous season's profits. $\boldsymbol{W'}_{it-1}$ consists of previous growing season's weather variables including hours of exposure above heat stress and below the cold stress thresholds, and soil moisture content. $\boldsymbol{V'}_{it-m:t-1}$consists of crop-specific moving climatic averages for temperatures and soil moisture during the growing season over a 29-year period.

Weather and climatic variables are assigned based on crops' growing season: spring crops are assigned weather from the spring growing season, while winter crops are assigned weather of winter growing season. Due to collinearity between spring and winter season weather and climate variables, $\boldsymbol{W'}_{it-1}$ incorporates extreme temperature metrics (heat and cold stress) from both seasons but includes only spring season soil moisture. Similarly, $\boldsymbol{V'}_{it-m:t-1}$ includes moving averages solely for the spring season's temperature and soil moisture. Including all weather and climatic variables in the model leads to convergence issues, motivating the selective inclusion approach adopted in this study.

$\boldsymbol{X'}_i$ contains field characteristics including field size, elevation, soil quality, and access to irrigation. Year trends are included, a crop-specific fixed effect, τ_k, and field by year random effects are also controlled for in the analysis.

The spatial and temporal variation that is present allow for the estimation of a panel conditional logit model, which accounts for repeated choices at different periods of time. If $\varepsilon_{k,it}$, a random error term, is assumed to follow a type I extreme value distribution, then the probability of choosing the kth crop can be rewritten as

$$\rho_{ikt} = \frac{e^{\pi_{k,it}}}{\sum_{k=0}^{K} e^{\pi_{k,it}}} = \frac{e^{\pi_{k,it}}}{1 + \sum_{k=1}^{K} e^{\pi_{k,it}}} \qquad (5)$$

where the parameters can be estimated by maximum simulated likelihood (Stata, 2023). Controlling for field by year random effects relaxes the assumption of independence of irrelevant alternatives (IIA) to a degree by allowing correlation between choices over time (McFadden & Train, 2000). This is a significant benefit as the IIA assumption is unrealistic in the context of repeated choices of field crops over time. We employ a panel conditional logit framework also provides us the opportunity to simulate the effects of climate change. For inference, we also cluster the standard errors at the village level.

There are some potential identification concerns regarding our analysis. Weather can be endogenous to crop choices particularly if it is influenced by the actions of an individual farmer. This concern is more relevant for soil moisture as certain crops can influence the amount of moisture that is retained in the soil (Mendis et al., 2022). We use lagged growing season weather variables which are unaffected by farmers' future crop choices. Additionally, our soil moisture estimates are derived from the SWAT+ model at a more aggregated subbasin-level. Soil moisture the aggregated subbasin level is largely determined by the interaction of temperature and hydrological components and is unlikely to be influenced by individual farmer behavior.

Crop choices may be influenced by unobserved economic and political factors. We explicitly control for field characteristics including size, elevation, and access to irrigation, that can play an important role in shaping crop choices. We include a linear time trend to control for any unobserved factors that affect weather and crop choices simultaneously. Finally, we include field by year random effects to account for any regional effects that are correlated with weather.

We do not explicitly model crop rotations, although they can influence crop choice by linking current decisions to past planting and by affecting soil health, yields, and profitability. However, in our dataset, there are no dominant or well-defined rotation patterns, as shown in Table 1 below. Additionally, we account for rotation-related effects indirectly by explicitly controlling for profits, which capture much of the agronomic and economic impact of rotations. We also plan to run a specification that includes lagged crops.

	Maize	Wheat	Soybean	Sunflower	Oilseed	Fallow
Maize	0.37	0.25	0.15	0.23	0.0022	0.0018
Wheat	0.56	0.19	0.061	0.15	0.044	0.0016
Soybean	0.50	0.18	0.28	0.029	0.0023	0.00087
Sunflower	0.33	0.62	0.013	0.038	0.0044	0.00049
Oilseed	0.35	0.51	0.039	0.065	0.045	0.00034
Fallow	0.13	0.096	0.026	0.023	0.00082	0.73

Table1. Conditional Probability Matrix of Crop Transitions. This table shows the conditional probability matrix of crop transitions from 2016-2022. We drop all fields consistently classified as non-agricultural land (category 20) throughout 2016–2022, as well as fields that exited agriculture (land classified as 20 consecutively from 2020–2022). Observations where the crop planted was sugar beet or other crops are also excluded. For each current crop, we identify the probabilities of transitioning to all possible subsequent crops. Our results show that no dominant rotation exists in the data. In fact, farmers in Serbia have diverse cropping strategies.

Finally, it is important to note that the outside option in our crop choice model is leaving land fallow. We do not model the choice to move to a specialty crop or to exit agriculture. We drop all fields that are classified as non-agricultural or "other crops" as these alternatives are fundamentally different field crops choices. Specialty crops often involve long-term investments making it difficult to compare their profits directly to profits earned by field crops. Similarly, exiting agriculture may involve a lump-sum payments, which are not comparable with annual profits earned by field crops. Our model specifically focuses on capturing switching decisions between planting field crops and leaving land fallow in response to climate change and does not account for longer-term exit decisions We believe this limitation does not significantly affect our findings since only 0.02% of fields growing field crops were left fallow for three consecutive years during 2018–2022, indicating minimal permanent exit. Furthermore, under extreme drought conditions in 2017, 2021, and 2022, only 0.7% of fields were left fallow. This suggests that land abandonment due to drought or climate stress has historically been limited, supporting the assumption that permanent exit is not a major factor within our study period. While recent demographic data indicate a 6% decrease in agricultural land between the 2018 and 2024 censuses (Agroberichten Buitenland, 2024), future research could incorporate more detailed scenarios of agricultural exit as demographic and economic transitions evolve.

1.4 Data

Yield data

We obtain pixel-level data on observed yields[2] from 2017-2022 for six crops, maize, soybean, sugar beet, sunflower, wheat and rapeseed, for Vojvodina region (Bisosense, 2024). Each pixel is

[2] Fields with no yield data are not considered in the analysis. Most fields having missing yield data are classified as non-agricultural land.

216.07m×216.07m and represents yields in tons per hectare. Since we want to model decision-making at the field-level, we convert the pixel to field-level yield data (details are provided in Supplementary information S1. A).

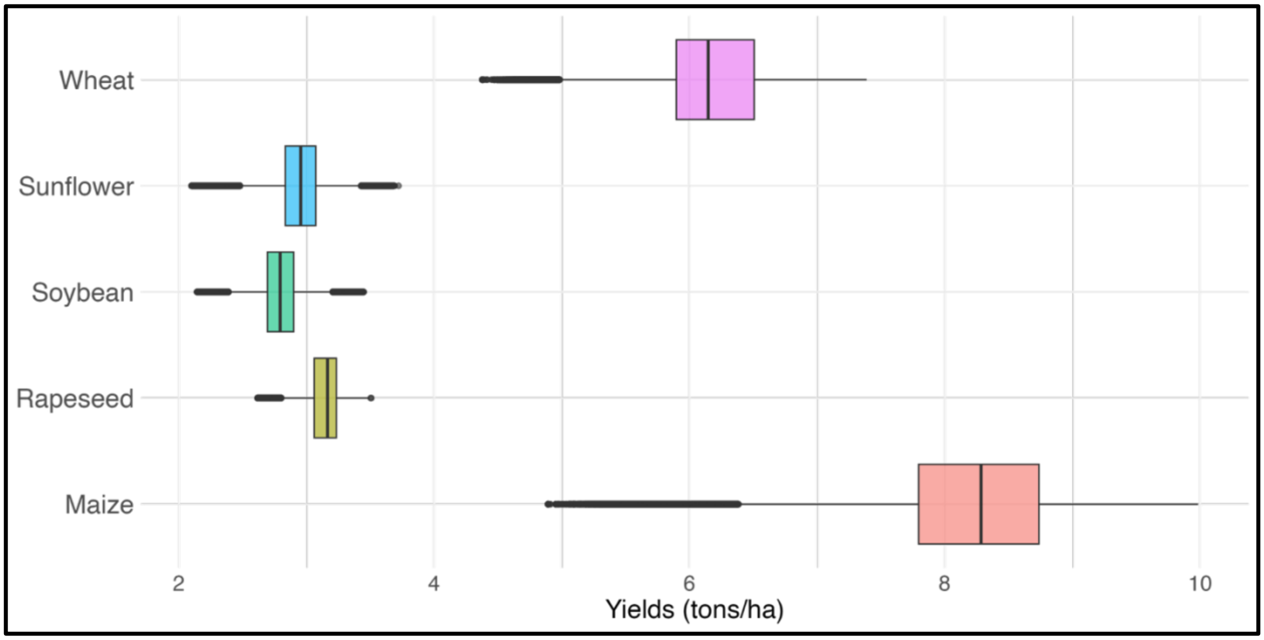

Figure 2. Crop Yields Distributions (2017-2022). This figure shows the variation is yields within and across crops. We pool every field's annual yield observation from 2017 through 2022, so that both cross-sectional (field-to-field) and temporal (year-to-year) variation are shown. Maize and wheat tend to have the highest variability in yields. Soybean, sunflower, and rapeseed tend to have tightly clustered yields.

Crop data

Pixel-level annual planting data for six major crops is obtained from Landsat and Sentinel-2 images for 2018-2022 with an accuracy of over 90% for each year (Živaljević et al., 2024). Each pixel of 10 m x 10 m dimensions is categorized into maize, wheat, soybean, sugar beet, sunflower, rapeseed, other crops – a single crop category that consists of orchards, vegetables, alfalfa or clover - or non-agricultural land. While the pixels are located across all of Serbia, 95% of the pixels in our analysis are in Vojvodina as agriculture is mainly present in this region.

Pixel-level data on crops is converted into field-level data using a cadastral map of field boundaries in Serbia. Our decision to move from pixel to field-level data is justified as planting decisions are often made at the field-level. For classifying the field into one of the crop categories, we use the crop that is planted on the majority of pixels within the field's boundaries. However, in doing so, we might be introducing some crop-specific bias, particularly affecting crops traditionally planted as secondary crops. To ensure that such crop-specific bias is not present in our analysis, we compare the percentage share of crops covered under pixel vs field-level data. Details on data construction and the test for crop-specific bias can be found in the supplementary text (S1. B).

We drop land classified as non-agricultural land is also removed from the dataset (37% of fields get dropped). Fields classified as "other crops" and sugar beet from our final dataset. Other crops are dropped due to their heterogenous nature as high-value crops are lumped together with low-value crops (29% of fields get dropped). Sugar beet is excluded because profit data for this crop are unavailable; however, since it is planted on 1.6% of fields, its removal is unlikely to affect results significantly. Additionally, fields presumed to have exited agriculture—identified as those left fallow for three consecutive years (approximately 0.02% of the sample)—are excluded. The final dataset is an unbalanced panel of 1473701 fields. Year-wise field-specific shares are presented in the supplementary materials.

Temperature Data

Data on daily maximum and minimum temperatures in degree Celsius are obtained from E-OBS from 1988-2022 (Cornes et al., 2018). This high-resolution (0.1°) gridded dataset is interpolated from meteorological observations from weather. The minimum temperature reported from 1988-2022 is -34°C and the maximum temperature reported is 45°C. August is the hottest month in Serbia and January is the coldest month.

For the yield weather model, we use daily maximum and minimum temperatures from 2017 onwards to obtain total hours obtained in 3°C bins. To estimate hours of exposure, we replicate sine function approximation method adopted by Ortiz-Bobea et al. (2019) to convert daily minimum and maximum temperatures into 15-minute interval estimates. The number of 15-minute intervals within each temperature bin is counted for each month and then converted to hours. These monthly exposure hours are aggregated over the growing season to obtain total hours of exposure per bin. Finally, to reduce noise from sparse data, we aggregate bins with negligible exposure and combine 1°C bins into broader 3°C bins.

In our crop choice model, we include both short and long-term temperature variables that can influence farmers' crop choices. To capture the impact of fluctuations in recent temperatures, we include heat and cold stress variables. We rely on temperatures from the previous year's growing season because at the time farmers make their planting decisions, information about the current year's growing season is not yet available. Consequently, farmers base their expectations for the current year's weather on historical temperatures. We include variables on extreme temperature events in our crop choice model. We believe that including extreme temperatures is crucial as farmers experiencing extreme heat or cold temperatures in the previous season may switch to more tolerant crops. Crop-specific thresholds on extreme temperatures are identified from the yield-weather models. These thresholds are incorporated to create crop-specific heat and cold stress variables that represent the total number of hours crops are exposed to temperatures above the heat and below the cold thresholds during the previous growing season. Along with short-term temperature measures, we include 29-year moving historical averages of mean temperature to account for regional climatic differences influencing crop suitability. Details on the construction of temperature variables for the yield and crop choice model are presented in Supplementary text (S1.C).

Soil Moisture

Data on monthly soil moisture is obtained from running Soil and Water Assessment Tool-Plus (SWAT+), a semi-distributed, process-based hydrologic model, using daily data on precipitation, temperature, humidity, and solar radiation (Jalali, et al., 2025). Monthly data is converted to yearly averages by using means soil moisture for the growing period. Soil moisture during the current growing season is incorporated into the yield-weather model as average values computed across distinct growing stages. Soil moisture for previous growing season and the 29-year moving historical average growing season soil moisture are included in the crop choice model. Details on the construction of the variables are provided in the Supplementary text (S1.D).

Profits

Crop-specific profits are constructed using field-level data on observed yields from 2017 to 2022 and country-level crop prices (FAO, 2025). For each field, revenue is calculated as the product of crop yield and price. To obtain annual crop-level revenue estimates, we aggregate field-level revenues using a weighted average, where each field's contribution is weighted by its area. This approach ensures that larger fields—which contribute more to total production—have proportionately greater influence in the overall revenue estimates. The revenues are then subtracted with costs of production data obtained from a survey of 728 for the period of 2015-2020 (BioSense Institute, 2022). Crop-specific costs of production include raw material costs for seed, fertilizers and pesticides, and machinery and labor costs for sowing, tillage, fertilizer and pesticide application, and harvest. As we utilize profits from the previous year in our crop choice model, we need profit data spanning from 2017 to 2021. However, since our survey data only extends through 2020, we use inflation-adjusted costs for 2021. Additionally, any missing cost values within the survey period are interpolated using the same approach.

Field Attributes

Data on soil quality for the subbasins in the Danube Water shed is obtained from Harmonized World Soil Database (Fischer, et al., 2008) that contains data on worldwide different soil mapping types. Available water capacity is used to represent the soil quality – details are provided in supplementary text (S1.E). Data on elevation are obtained from a digital elevation model (European Environment Agency, 2019). Field area is calculated using the field boundaries in the data. To construct a variable on access to irrigation, we use pixel-level data on irrigation status of maize, soybean, and sugar beet from 2020-2022 Radulović, et al., 2023). We convert pixel-level irrigation data to field-level data using field boundaries. A field is classified as irrigated if 50% more pixels within the field's boundary are irrigated. To create an indicator variable of irrigation access, we assume that if a field is irrigated in any year during the 2020-2022 period, it is considered to have access to irrigation for all the years included in our analysis.

Simulations of Climate Change Impact on Yields and Crop Choices

For our climate change scenarios, we obtain EURO-CORDEX data on bias-adjusted regional climate simulations (Dosio, 2016). This dataset includes downscaled Global Climate Model (GCM)-Regional Climate Model (RCM) simulations that provide daily time series future weather projections from 1981-2100 for CMIP5 RCP 4.5 and 8.5. Five distinct climate models were run under both RCP scenarios – details are provided in Table 2 below.

Institute	RCM	Driving GCM
CLMcom	CCLM4-8-17	CNRM-CERFACS-CNRM-CM5 ICHEC-EC-EARTH MPI-M-MPI-ESM-LR
IPSL_ INERIS	WRF331F	IPSL-IPSL-CM5A-MR
KNMI	RACMO22E	ICHEC-EC-EARTH

Table 2. Bias-adjusted GCM-RCMs Utilized in SWAT+ model Simulations. Source: (Dosio, 2016).

We utilize future daily temperature projections for RCP 4.5 to construct ensemble mean temperature data across five climate models. Similarly, simulations outputs for the five distinct climate models obtained from the SWAT+ model were used to obtain ensemble mean of soil moisture data. Overall, future projections show an increase in mean temperatures and a decrease in precipitation compared to the observed, historic (1991-2020) weather data.

We investigate the impact of climate change on yields and crop choices using the future climate data in the midcentury: 2040 - 2070. For the yield model, our simulations allow us to predict field-level crop yields during 2040-2070 period conditional on field characteristics and static year trends. In the crop choice simulations, we update the short and long-term weather variables with future weather projections. Heat stress, extreme cold and soil moisture variables for the previous growing season are updated using the future data. 29-year moving historical averages are also updated accordingly. We also incorporate the effects of climate-induced changes in yields. We include a scenario under which simulated yields are utilized to construct future crop-specific profits. Predicted field-level yields are multiplied by baseline crop prices to obtain field-level revenues, which are then aggregated to annual, crop-level revenues using area-weighted averages. Finally, baseline production costs are subtracted from these projected revenues to yield future profits. Assuming baseline prices under climate change is a strong assumption. To relax the assumption of constant prices, we are currently running an additional scenario in which crop prices adjust to reflect yield shocks.

In our simulations, we only adjust weather, climate, and profit variables to reflect projected climate change, while holding fixed year trends, production costs, and other factors capturing technological and broader economic conditions at their baseline levels. This approach isolates the effect of climate by attributing differences between the baseline and simulated periods solely to climate-driven changes (Arora et al., 2019). Accordingly, our projected yields and crop choices are not unconditional forecasts of the future; rather, they indicate how yields and cropping decisions respond to changing climatic conditions, holding other determinants constant.

1.5 Results

1.5.a Yield Weather Model Results

The results from our yield weather models are provided in Table 3 below - full regression results can be found in Supplementary text (S2. Table 1 & Table 2). Our yield-weather models reveal that extreme weather thresholds vary tremendously across crops. Yields for spring crops tend to start declining at temperatures lower than 4°C and temperatures above 34°C. For instance, an additional hour of exposure to temperatures above 34°C will decline yields by 0.2% for maize relative to base category of 16 to 19°C. Sunflower exhibits higher heat tolerance, as yields do not significantly decline until temperatures exceed 40°C (Debaeke et al., 2017).

Yields for winter wheat and rapeseed tend to decline at temperatures above 28°C. Specifically, an additional hour of exposure above 28°C reduces wheat yields by about 0.2%. The lower temperature thresholds for winter crops show unusual patterns; for instance, wheat yields do not decline until temperatures drop as low as -14°C. We suspect this result is due to the low number of exposure hours in the temperature bins below freezing.

	Maize	Soybean	Sunflower	Wheat	Rapeseed
Spring Crops					
Cold Stress (< 4°C)	- 0.0006**	-0.002***	-0.0008***	-	-
Heat Stress (> 34°C)	-0.003***	-0.015***	0.002***	-	-
Early Season Soil Moisture (Apr-May)	1.62e-05	-0.0004***	0.0005***	-	-
Growing Soil Moisture (June-Aug)	0.001***	0.001***	0.0003***	-	-
Harvesting Soil Moisture (September)	-0.002***	-0.003***	-0.0006***	-	-
Winter Crops					
Cold Stress (< -5°C)	-	-	-	0.0008***	0.0012***
Heat Stress (> 28°C)	-	-	-	-0.0007***	-0.0004***
Early Season Soil Moisture (Oct-Feb)	-	-	-	-0.0013***	-0.0003***
Growing Soil Moisture (March-May)	-	-	-	0.0005***	0.0005***
Harvesting Soil Moisture (June)	-	-	-	0.0002***	4.44e-05

Table 3. Marginal Effects of Temperature and Soil Moisture on Crop Yields. The table present the marginal effects of temperature bins and soil moisture for different growth stages on crop-specific yields. The results are from a two-way fixed effects estimation that controls for field fixed effects. Standard errors are clustered at village-level. Significance and confidence intervals are obtained from bootstrapping with 9,999 replications. The results show the thresholds of extreme weather vary significantly across crops.

Overall, our findings on extreme temperature thresholds align with previous literature. The upper temperature threshold for spring crops generally falls between 30°C and 35°C. Maize yields tend to decline at temperatures around 29–30°C, while soybeans are typically more heat-tolerant, with yield declines occurring above 32°C (Miao et al., 2016; Ortiz-Bobea et al., 2019). Interestingly, we find that maize and soybean yields decline at similar temperature ranges in our data. This can be explained by the differences in crop varieties as Serbian farmers mainly use domestic cultivars (Agroberichten Buitenland, 2020). Our results also remain robust to different specifications (1-degree and 2-degree temperature bins). Notably, we find soybean to be much more responsive to temperature changes with significantly larger coefficients on both, beneficial and harmful bins.

Results for winter crops are slightly different from the existing literature. While winter wheat yields start declining at temperatures above 25°C (Ortiz-Bobea et al., 2019), we find wheat to be more heat tolerant as evidence points that Serbian wheat exhibits higher resilience under climate stressors (Mirosavljević et al., 2024).

Our yield model demonstrates good prediction accuracy, significantly improving over a baseline model with only year trends and fixed effects – as observed by the reduction in root mean squared error (RMSE) (Figure 3). However, the degree of improvement varies across crops. Soybean shows the highest increase in prediction accuracy, followed by rapeseed and maize. Our yield model's performance aligns with existing literature, showing slightly improved accuracy. For example, Ortiz-Bobea et al. (2019) report a maximum RMSE reduction of around 20%, which is comparable to or slightly lower than our results. The relatively low RMSE for sunflower implies that weather does not explain variation in sunflower yields as much as it does for other crops. This is consistent with historical data from 2006–2023 (FAO, 2025), where sunflower yields remained relatively stable despite multiple drought years.

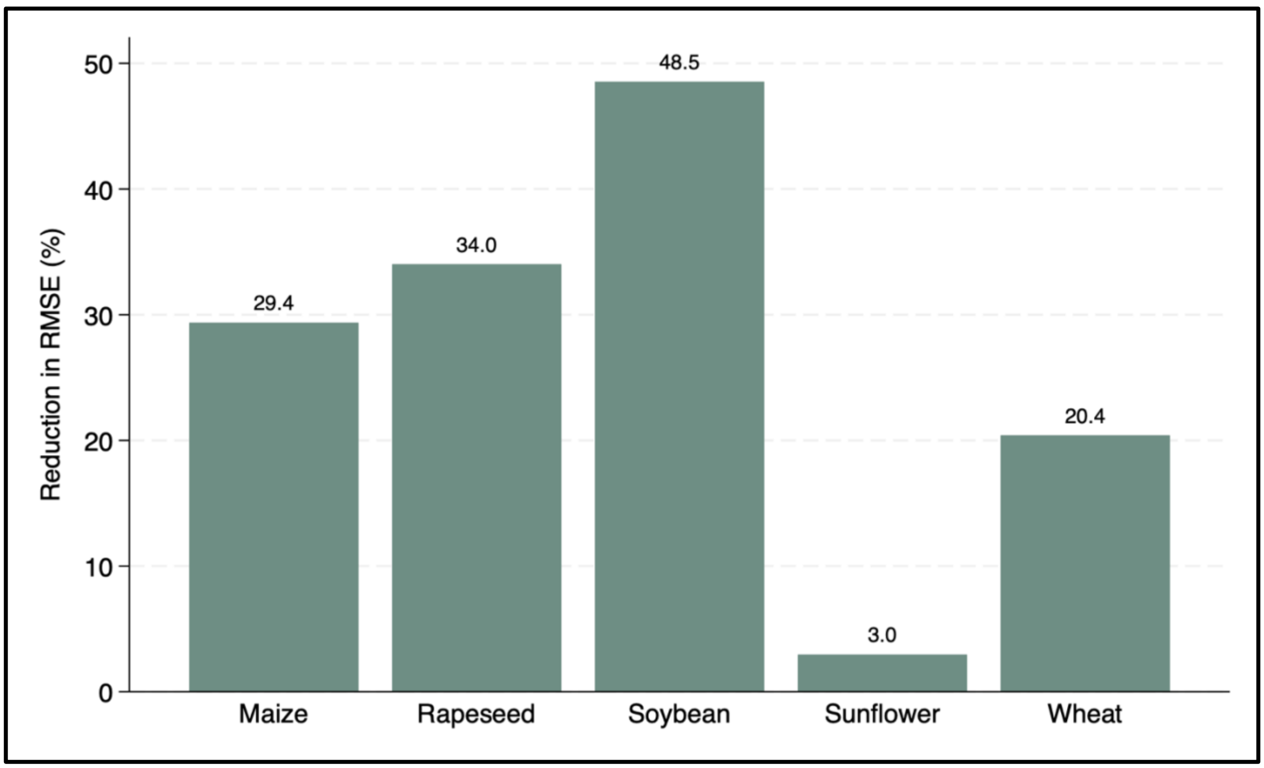

Figure 3. Yield Model Prediction Accuracy Across Different Crops. The figure shows the reduction in root mean squared error (RMSE) of our yield model relative to a baseline with only year trends and fixed effects. Out-of-sample accuracy is assessed using 10-fold cross-validation at the field level. Soybean achieves the largest gain (49% RMSE reduction), followed by rapeseed (34%) and maize (29%). Wheat shows moderate improvement, while sunflower exhibits the least, suggesting weather variables explain less of its yield variation.

1.5.b Climate Change Impact on Yields

To evaluate the implications of climate change on crop yields, we replace climatic variables in our baseline yield-weather regressions with future weather to predict field-level yields. The results are presented in Figure 4 below.

Our results from the yield-weather simulations provide some interesting insights. We find that climate change impacts on yields vary significantly across crops. Maize remains the most affected crop with consistent decline in its yields across all simulation periods. In most blocks, the confidence intervals are below zero – indicating meaningful decline in yields.

Soybean is particularly interesting. The crop's yields are projected to decline by almost 20% in 2040-2045 simulation period, then increase by almost 20% from the baseline in 2045-2050 simulation period. The changes are more moderate post 2050-2055 simulation blocks, and the prediction is also with higher uncertainty.

The differences in the response of maize and soybean yields to climate change are particularly fascinating. The initial gains in soybean yields can be explained by the results from the yield-weather model and the projected climate conditions. The period from 2040-2055 is projected to have moderate warming, with a shift away from colder temperatures and an increase in hours of exposure to temperatures ranging from 7-25°C. Since soybean yields are highly responsive to these temperatures (as observed from the large regression coefficients) – these changes are likely to positively impact yields in the early future periods. In contrast, for maize, the benefits from increased exposure to beneficial temperature bins are much smaller and are outweighed by losses due to greater exposure to harmful high temperatures. Additionally, differential responses to soil moisture during key growth stages also contribute to the divergence in yield outcomes between the two crops.

Sunflower yield changes are relatively stable with changes relatively between -1% to +4% – pointing to the crop's resilience. There is also uncertainty in prediction. Changes in wheat yields are also relatively modest ranging between 0-5%.

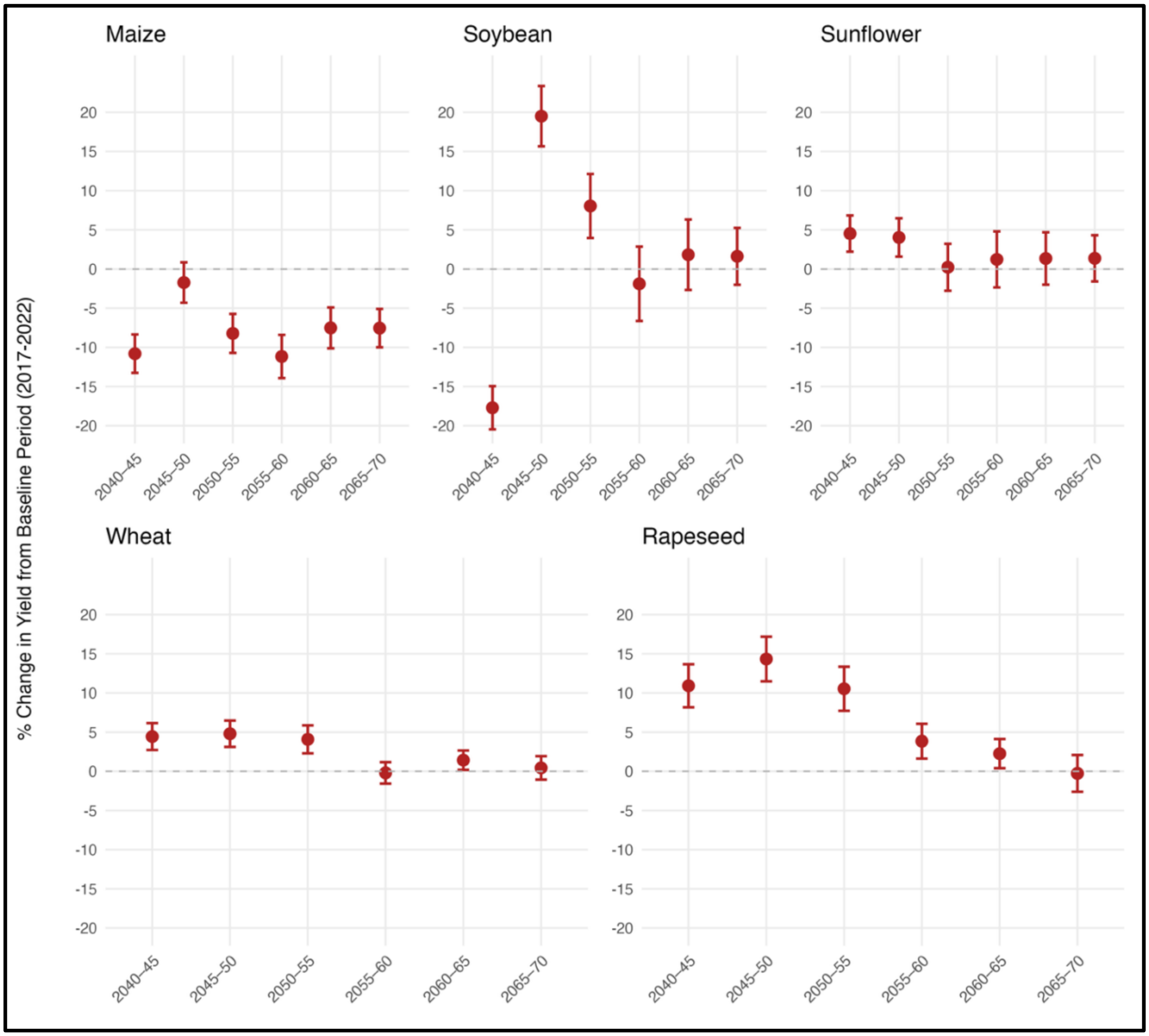

Figure 4. Predicted Change in Crop-specific Yields (%) Relative to the Base Period (2017-2022). This figure shows the changes in average yields for each simulation block relative to the base period. For each field, baseline yields are predicted with observed weather, and future yields are predicted by replacing weather covariates with the block-specific future weather while holding the non-weather trend fixed at the baseline average year. Uncertainty from estimation of regression parameters is represented through the confidence intervals. Overall, we find maize shows persistent declines, soybean exhibits mid-century gains, wheat effects are modest, and sunflower changes are small and often indistinguishable from zero.

Results for the yield responses under climate change are drastically different from what is found in the literature particularly, for soybean and winter wheat. Studies focused on the US find soybean and wheat yields to decline significantly due to warmer and drier conditions predicted under climate change (Yu et al., 2021; Tack et al., 2015).

Our results in fact align closely with the literature focusing on Serbia. Climate change impact assessments in Serbia project increases in soybean and wheat yields. For instance, Jančić et al.

(2015) find soybean yields to increase by 20-50% by mid-century in many locations. Likewise, wheat yields are predicted to increase under climate change (Mihailović, et al., 2014).

1.5.c Crop Choice Model Results

Results from the crop choice model are presented in Table 4. We report the coefficients from the conditional logit model, as average partial effects are generally less informative in the context of climate change analysis. The estimated log-odds ratios provide clear insights into both the direction and statistical significance of the effects. Complemented by our simulations, these results illustrate how various weather variables interact and jointly influence crop choice decisions. We are currently computing average partial effects for field-level attributes; however, given the model's high computational complexity, these results are still in progress. All results are presented relative to the outside option of leaving the land fallow.

Lagged crop-specific profits have a positive impact on the likelihood of planting that crop. This means that if the profits realized from planting a crop in the previous year increase, the likelihood of choosing that crop in the current year increases.

Turning to field-specific attributes, we find that an increase in heat stress days during the spring growing season reduces the likelihood of planting all crops. In other words, as days with extreme heat during the spring increase, farmers are more likely to leave land fallow rather than risk planting. Similarly, an increase in cold stress days during the winter growing season also reduces the likelihood of planting. This is intuitive, as Serbia's spring and winter growing seasons overlap: colder winter days can delay spring planting through frost and other constraints. Spring cold stress days further reduce the likelihood of planting all crops (except for sunflower), although the estimated effect for sunflower is not statistically significant.

Interestingly, heat stress days during the winter growing season increase the likelihood of planting both spring and winter crops relative to leaving land fallow. This somewhat counterintuitive result can be explained by the timing: exposures to temperatures greater than 28°C primarily occur from June onward, coinciding with the end of the winter crop season. As winter crops mature from October to June, heat stress is experienced mainly around harvest. Warmer end-of-season conditions can promote timely maturation and facilitate harvest (Perez et al., 2023). Moreover, exposure to temperature exceeding 28°C in early growing season is ideal for crop growth thereby, explaining the increase in the probability of planting spring crops (Minoli et al., 2022).

Long-term climatic trends in spring season temperatures play a significant role in shaping crop choices. An increase in historic spring season temperatures raises the likelihood of planting winter crops; rather than leaving land fallow, farmers tend to switch to winter crops under warmer spring conditions. Similarly, the probability of planting sunflower rises with higher historic spring temperatures, relative to leaving land fallow, reflecting the crop's resilience. The positive coefficient for maize is not unexpected as maize is historically grown in places with warmer temperature.

The results from previous spring growing season are opposite to what we expected. An increase in previous spring growing season's soil moisture reduces the probability of planting all crops, suggesting that farmers are more likely to leave land fallow. We believe these results are attributable to the strong correlation between previous growing season's soil moisture and historical average for growing season's soil moisture ($\rho = 0.7$). Our hypothesis is also confirmed by the sign on the long-term trends in spring growing season soil moisture; wetter spring conditions increase the probability of planting crops relative to leaving land fallow. Winter crops also benefit from wetter spring season due to the overlapping growing seasons. To address this, we have replaced previous growing season's soil moisture with an indicator of soil moisture anomalies which captures deviations from long-term moisture conditions; positive values indicate wetter-than-normal conditions, while negative values indicate drier-than-normal conditions. The updated results will be available in the revised version.

Variable	**Conditional Logit**				
Lagged Profits	0.0000104***				
	(0.0000024)				
Crop-Specific Results	**Maize**	**Soybean**	**Sunflower**	**Wheat**	**Rapeseed**
Spring Season Heat Stress	-0.0032***	-0.0033***	-0.0086***	-0.00332***	-0.00298*
	(0.0007)	(0.000860)	(0.000969)	(0.000672)	(0.00163)
Winter Season Heat Stress	0.0054***	0.0112***	0.0115***	0.0076***	0.0059***
	(0.001)	(0.0009)	(0.0008)	(0.00075)	(0.0013)
Spring Season Cold Stress	-0.011***	-0.0072***	0.0015	-0.0021**	-0.0041**
	(0.0025)	(0.0023)	(0.0012)	(0.00088)	(0.0019)
Winter Season Cold Stress	-0.0021***	-0.006***	-0.0014***	-0.0017***	-0.0032***
	(0.0004)	(0.00045)	(0.0004)	(0.0004)	(0.00057)
29-year Moving Average Spring Temperature	1.224***	-1.96***	2.247***	1.114***	-0.74**
	(0.19)	(0.31)	(0.24)	(0.21)	(0.35)
Spring Season Soil Moisture	-0.0183***	-0.0228***	-0.0137***	-0.0133***	-0.026***
	(0.0015)	(0.0018)	(0.0018)	(0.0015)	(0.0027)
29-year Moving Average Spring Soil Moisture	0.02***	0.036***	0.011***	0.013***	0.0111***
	(0.0024)	(0.0027)	(0.0026)	(0.0022)	(0.0039)
Observations	36019302				

Table 4. Coefficients from Crop Choice Model.
Baseline option is leaving land fallow. All coefficients are relative to land left fallow.
Coefficients on field attributes and crop-specific coefficients are not included in the Table.
Robust (clustered by municipality) standard errors are in the parentheses.
*** p<0.01, ** p<0.05, * p<0.1

To assess the predictive accuracy of the crop choice model, we perform a three-fold cross-validation procedure that randomly partitions the data into training (70%) and test (30%) subsets by case. For each iteration, the model is re-estimated on the training sample, and out-of-sample accuracy is evaluated using classification accuracy—the percentage of cases in which the model's predicted choice, Brier score, and the log loss. Due to the computational intensity of this procedure, the model validation is still in progress, and the results will be included in the revised version of this paper.

1.5.d Climate Change Impact on Crop Choices

To evaluate the implications of climate change on crop choice, we conduct two simulations: (1) a "climate change only" scenario, in which only the weather and climate variables in the crop choice model are updated, and (2) a "climate and yield change" scenario, where we also update profits using simulated field-level yields, calculated by multiplying future yields by baseline crop prices and subtracting baseline costs.

The results from the "climate change only" simulation are presented in Figure 5. The results reveal interesting patterns in crop substitution. Under changing climate – warmer and drier conditions – farmers are likely to reduce planting spring crops as evident from the high decline in probability of planting soybean. We find farmers to be switching not only across season but also within season. Sensitive crops such as soybean and rapeseed are replaced with the resilient sunflower and wheat.

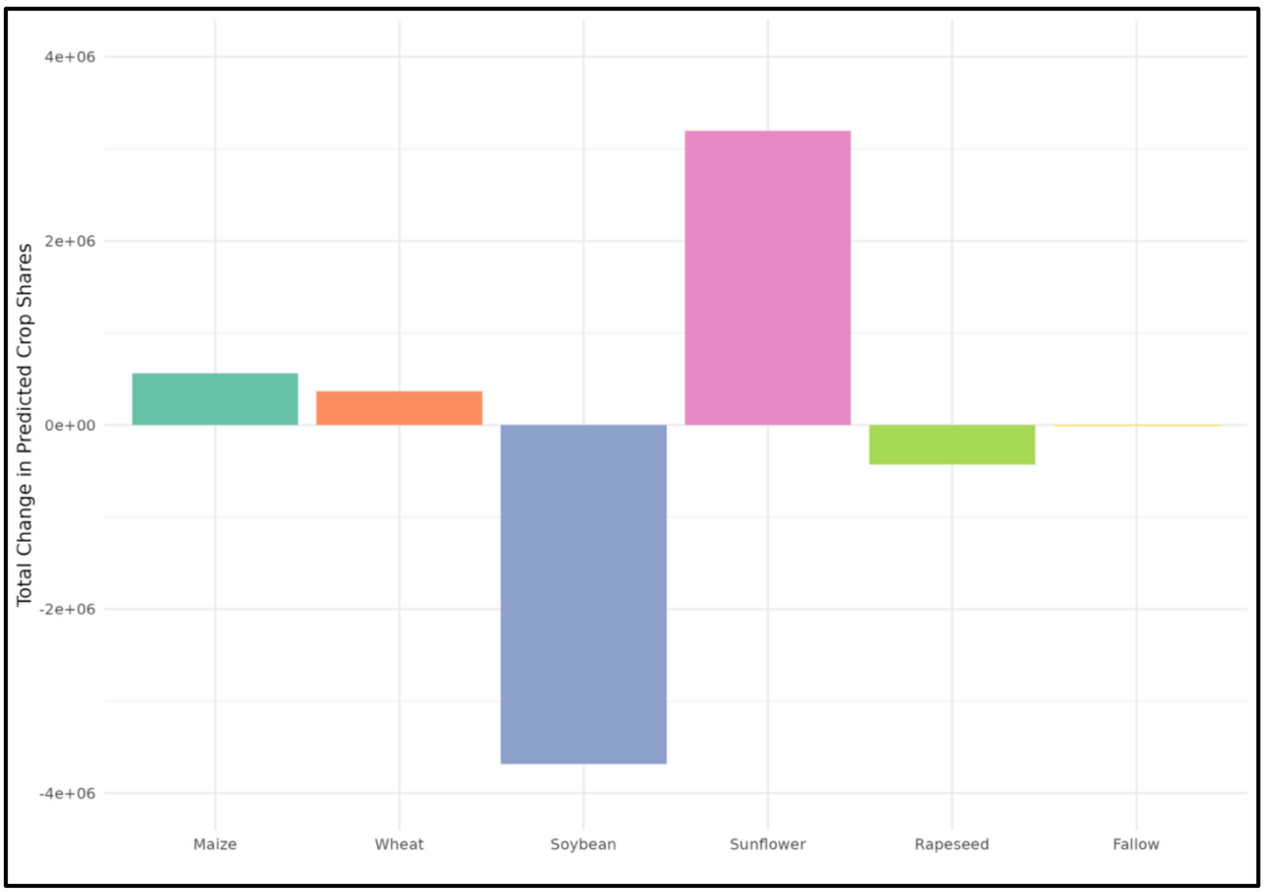

Figure 5. Change in Predicted Crop Shares under Climate Change Only Simulations from 2040-2070 relative to Baseline (2018-2022). This plot shows projected changes in crop shares under climate change, with the change calculated for 2040–2070 relative to the baseline period 2018–2022. Crop shares are

simulated using a crop choice model with future climate projections. Results suggest farmers switch away from climate-sensitive crops (soybean, rapeseed) toward more resilient crops (sunflower, maize, wheat).

Farmers' crop choices are shaped not only by climatic conditions but also by expected profitability, which itself can be altered by climate change. To account for such feedback loops, we run the "climate and yield change" scenario; the results are presented in Figure 6. Comparing these findings with the climate change only simulation (see Figure 5), we observe several notable differences: (1) maize crop shares decline; (2) the decline in soybean share is attenuated; and (3) the increase in wheat share is larger than in the climate-only scenario.

These results align with our expectations. Our yield simulations indicate that maize yields are predicted to decline significantly under climate change. Assuming constant prices, this will adversely impact future profitability of maize, forcing farmers to switch away to from maize. The smaller decline in soybean shares stems from an increase in its expected profitability, as soybean yields are projected to experience a modest increase under climate change. The increase in wheat shares is larger compared to the climate change only simulations as wheat yields remain relatively stable under future climatic conditions, making the crop more attractive to farmers. Lastly, the small decrease in land left fallow under both simulations indicates that farmers would switch to more resilient crops rather than leaving their land fallow. This is corroborated with the baseline data where only 0.4% of fields are left fallow from 2018-2022.

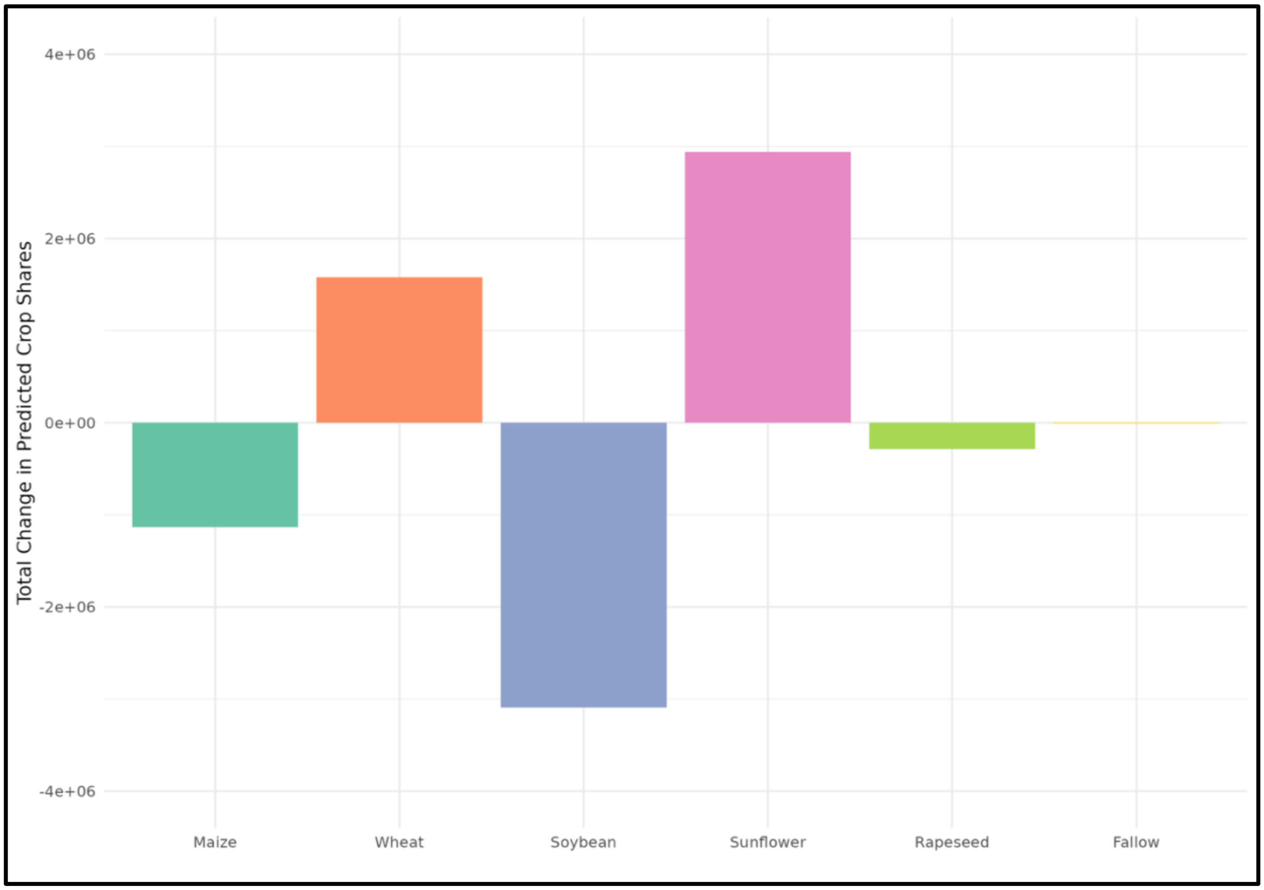

Figure 6. Change in Predicted Crop Shares under Climate Change & Yield Change from 2040-2070 relative to Baseline (2018-2022). This figure shows projected changes in crop shares under scenarios with both climate change and yield change. Crop shares are simulated using a crop choice model with future climate projections and yield projections are utilized to calculate future profits. Results indicate that farmers are likely to switch away from profitable crops such as maize, soybean and rapeseed and adopt more resilient crops such as sunflower and wheat.

In the simulations employed in the current version of this paper, we only change climate and profitability through yield changes (assuming prices remain constant). The assumption that prices remain unchanged is a strong one. Crop prices are likely to change in the future particularly in response to changes in yields. We are currently running a third simulation, "climate + yield and market adjustment" scenario, under which we incorporate both simulated yields and the corresponding price adjustments that arise from yield changes. Using an instrumental variables approach, we estimate that a 1% decrease in yields increases crop prices by 0.42%. This elasticity is then applied to adjust future prices based on deviations in simulated yields from baseline (2017-2022) average yields. Profits are recalculated using these simulated yields and prices, with costs held at baseline levels. Incorporating this simulation allows us to construct profit projections that account for both yield and price responses to climate changes. These extended simulations are underway and will be presented in the revised paper.

1.5.e Welfare Implications of Crop Substitution

Crop choices adjust significantly under evolving climatic and yield changes. Our simulations indicate that farmers switch away from maize and soybean to more resilient crops including sunflower and wheat. While this adaptive behavior helps buffer farmers against welfare losses, it is important to note that wheat and sunflower are generally less profitable than maize and soybean. As a result, this crop switching does entail welfare costs. Figure 7 below shows that welfare of farmers (as proxied by change in expected profit) under baseline conditions, and under the "climate-change only", and "climate and yield change" scenarios

Both scenarios show a more left-skewed welfare distribution, highlighting that farmers incur welfare losses when switching to less profitable crops. This emphasizes that crop switching does not fully offset the decline in welfare incurred due to changing climatic and market conditions. On average, we find welfare losses mounting to 25, 800 dinars/hectare (34% reduction in profits) under climate change only and 26,027 dinars/hectare (35% reduction in profits) under climate and market scenario from the baseline (current conditions).

It will be informative to compare these welfare changes against a no-adaptation scenario to quantify the extent to which crop-switching buffers the welfare losses induced by climate change. We are currently estimating welfare outcomes under a counterfactual in which farmers are constrained to maintain their baseline crop choices under future climatic and market conditions. This comparison not only isolates the value of adaptive behavior but also provides critical policy insights into how much of the climate-induced welfare loss can realistically be mitigated through behavioral adaptation alone. The results from this analysis will be presented in the revised version of the paper.

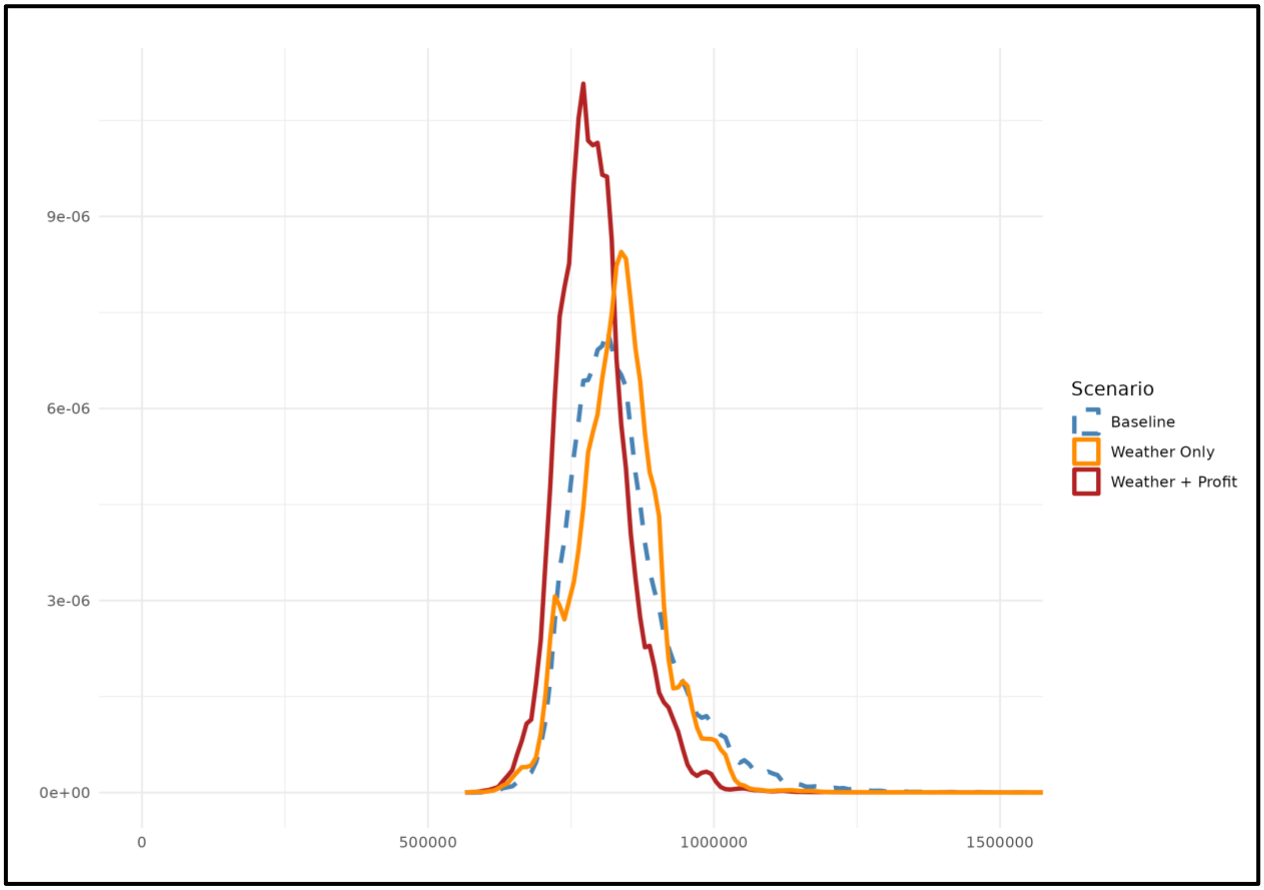

Figure 7. Distribution of Welfare Under Baseline and Climate Change Scenarios. This figure presents the estimated distribution of welfare under three scenarios: Baseline, Climate Change Only, and Weather and Profit. Welfare is proxied by change in expected profits. The density curves show that, while the distribution of welfare under climate change scenarios shifts leftward—indicating welfare losses—most farmers experience only moderate changes in consumer surplus compared to the baseline. The distribution is more left skewed in both climate change scenarios, reflecting that some farmers incur substantial welfare losses as they switch to less profitable crops.

1.6 Conclusion and Policy Implications

Climate change is increasingly altering weather patterns, impacting the suitability of crops traditionally grown in specific regions. Our study examines how farmers adjust their crop choices under evolving climatic and market conditions. Using rich field-level data on crop yields and crop choices, we identify the factors that shape crop choices and simulate substitution patterns under changes to short-term weather, long-term climate and expected crops profitability. First, we separately estimate yield weather regression models using two-way fixed effects for five crops in our data including maize, soybean, sunflower, wheat and rapeseed. The purpose of the yield model is: (1) to identify crop-specific threshold of extreme temperatures, (2) to predict yields under climate change, and (3) to estimate future crop profitability. Results from the yield weather model are then integrated into a crop choice model to identify the key variables influencing farmers' decisions and simulate how crop choices would evolve under "climate-change only" and "climate and market" scenarios.

Our yield-weather model reveals crop-specific thresholds for extreme weather. For example, maize and sugar beet yields decline at temperatures below 4 and above 34°C, whereas winter crop yields decline at temperatures above 28°C. Results from yield simulations indicate significant heterogeneity in yield responses across crops and fields. Maize is predicted to experience significant decline in yields whereas soybean, wheat, and sunflower may see modest gains. Our crop choice model shows, unsurprisingly, that profitability positively influences crop choice. Increase in the incidence of heat and cold stress reduces the probability of planting all crops, with farmers leaving land fallow. Long-term climatic trends also play a significant role with wetter conditions proving to be conducive for production of all crops. Our simulations reveal substantial crop switching to mitigate losses incurred under changing market and climatic conditions, with farmers switching away from profitable maize and soybean to resilient sunflower and wheat.

The vulnerability of the agricultural sector to climate change has raised interest on understanding how crop choices adapt under future climate scenarios. Our study benefits from being the first to study field-level farmers' crop choices and yields across Serbia, as well as being one of the largest, high-resolution studies of its type. Results from our estimations provide insights on how market conditions interact with climatic factors to determine cropping decisions and how these choices adjust under future market and climate scenarios. Overall, we find that while crop switching does not completely offset the reduction in welfare caused by climate change, it substantially mitigates the losses that would occur if farmers were unable to adapt.

These findings highlight the critical need to support farmers' adaptive capacity—through investment in climate-resilient crop varieties, market infrastructure, and agricultural extension—so that they can respond dynamically to evolving risks. From a policy perspective, our findings suggest several directions for supporting adaptation more effectively. First, well-designed price incentives can help buffer farmers against income losses by ensuring that the transition toward less water-intensive or climate-resilient crops remains economically viable. Second, strengthening markets for lower-profitability crops—through better storage, processing, and distribution systems—can stabilize returns and reduce risk. Finally, targeted irrigation investments or investments in drought-resistant varieties can enable continued cultivation of high-value crops in regions most vulnerable to rainfall variability, complementing adaptation through diversification. Together, these measures can reduce welfare losses from climate change, improve agricultural resilience, and promote more equitable outcomes for farmers operating under climate stress. Future research should also explore barriers to adaptation, as even the partial adjustment observed here depends on farmers' awareness, access to new technologies, and functioning markets.

Supplementary Information "Weathering the Change: Modeling Crop Choices in Response to Climate Variability"

S1. Data Construction and Descriptive Statistics

S1. A Creating Field-level Yield Data

To construct consistent field-level yield estimates for crops over time, we extract annual raster-based yield data for five key crops: maize, soybean, sunflower, wheat, and oilseed rape. For each crop, we utilize spatial raster layers corresponding to each year from 2017 to 2022. These raster layers contain gridded estimates of crop-specific yields across the study region.

First, we overlay the raster layer data with a cadastral map of field boundaries in Serbia. Next, we compute the annual field-level yield for each polygon by extracting the weighted average yield from the corresponding raster layer. Specifically, for each field (i.e., polygon), we calculate a weighted average of the raster cell values that intersect the field, using the fraction of each raster cell that lies within the field boundary as a weight. This approach accounts for the fact that field boundaries do not perfectly align with the underlying raster grid. Rather than assigning a single raster cell's value to a field, this method leverages all intersecting cells and assigns more weight to those with greater spatial overlap. If no valid (i.e., non-missing) yield values are found within a field, the corresponding yield value is recorded as missing. Missing yields are mostly found for fields classified into non-agricultural land. However, if any raster cells within the field boundaries have missing data indicating that no crop was planted, they are ignored in the weighted average calculations. This extraction results in a panel of annual yield estimates for each field and crop.

S1. B Creating Field-level Crop Data

Crop classification maps for the years 2018 through 2021 were obtained as spatial datasets with each raster layer representing spatially explicit crop types for a given year. To generate field-level crop choice data, a cadastral shapefile containing field boundaries was overlaid onto the crop maps. This step obtained crop types for each intersecting field polygons. Because a field polygon may intersect multiple raster pixels with varying crop classifications, we assigned the dominant crop type to each polygon by identifying the crop planted on the majority of pixels contained within the field's boundary.

As some crops are traditionally planted as secondary or intercropped varieties, aggregating from pixel-level data to the field level using the majority crop type may under-represent these secondary crops. To ensure that such crop-specific bias is not present in our analysis, we compare the percentage share of crops covered under pixel vs field-level data. The results are presented in Table 1. From the table, it can be observed that the crop shares under both units of analysis are very similar. However, discrepancies are more pronounced for more commonly planted crops. That said, we are not overly concerned about this potential bias, as monocropping is prevalent in Serbia (Jachia & Milovanović, 2022). In fact, 87% of fields in our data are classified into the crop category that covers more than 85% of the pixels within the field boundary.

Table 1 Percentage Share of Crops Planted by Unit of Analysis

	Pixel-Level	Field-level
Maize	16	19
Soybean	6	5
Sunflower	6	7
Wheat	11	12
Rapeseed	1	1

Table 1 compares crop shares between pixel-level and field-level data (2018-2021). We first calculate pixel-level shares by summing pixels for each crop category across all years, then dividing by the total number of pixels. For field-level shares, each field is classified based on the crop occupying the majority of its pixels, and shares are computed similarly. Crops shares are similar at pixel vs more aggregated field-level data. Only maize has slightly higher representation in the field data as compared to the pixel-level data.

To obtain our final dataset, we drop sugar beet and "other crops" from our dataset. We also exclude all non-agricultural land from our dataset. Table 2 below shows the yearly classification of fields across the crop type categories. Field crops include maize, wheat, soybean, sunflower and rapeseed.

Table 2 Classification of Fields by Crop Type and Year (Percentage Shares)

	Field Crops	Sugar beet	Other Crops
2018	79	2	19
2019	67	1.5	31
2020	70	1.0	29
2021	66	0.6	33.3
2022	64	0.9	35

Table 2 summarizes the share of fields classified as field crops, sugar beet, and other crops for each year from 2018 to 2022. To construct the table, we used our field-level crop data from 2018 to 2022 to calculate the percentage of fields falling into each crop category by year. Field crops include maize, wheat, soybean, sunflower, and rapeseed, while all other classifications are grouped as "other crops. The share of "other crops" is growing over time whole the share of sugar beet is declining over time. This acts as a justification to dropping these 2 crop categories from our final dataset.

From Table 2, it is evident that fields classified as "other crops" exhibit an upward trend with a steady increase from 2018 to 2022. Among fields classified as "other crops", approximately 14% of these fields were consistently categorized as 'other crops' across all five years. Additionally, only 10% of these fields were classified in the "other crops category" in only one year. This high degree of persistence suggests that a significant share of fields classified as "other crops" are likely perennial and unlikely to rotate within typical annual cropping cycles. Moreover, the heterogenous nature of this category - with no way to distinguish whether a field classified as other crops has a high-value or a low-value crop planted on it - introduces significant measurement error in the analysis. Given this ambiguity, we exclude observations for a field in the year it is classified as "other crops".

S1. C Creating Field-level Temperature Data

To assign our temperature variables to the fields in our data, we intersect gridded temperature data in raster format with the cadastral map of field boundaries. For each year, temperature rasters representing hours of exposure in different temperature bins are generated from interpolated daily temperature data and utilized in the yield model. Similarly, temperature rasters with average and extreme temperatures are constructed for the crop choice model.

Using spatial extraction tools, temperature values from temperature raster cells are assigned to the field polygons. Because field boundaries often overlap multiple temperature raster cells, we compute temperature metrics as weighted averages. Rather than assigning the value of a single cell to a field, we calculate weighted averages of temperature variables for each field polygon, where the weights represent the proportion of each raster cell that overlaps the polygon.

Approximately 4% of field polygons do not intersect with temperature raster cells. We utilize Inverse Distance Weighting (IDW) using the ten nearest neighboring fields to assign temperature values to these fields. Missing values are estimated as weighted averages of neighboring observations, where weights decrease with distance, assigning higher weights to geographically closer observations. While the choice of ten neighbors is arbitrary, we assess robustness by repeating the imputation with five and twenty neighbors. The resulting values remain identical in terms of mean, minimum, and maximum temperature, suggesting that our findings are not sensitive to the specific imputation parameter.

S1. D Creating Field-level Soil Moisture Data

The spatial extent of the SWAT+ model includes the watershed of the Danube River and its tributaries. The watershed is divided into subbasins, and outputs obtained from the model are at the subbasin level. This indicates that the soil moisture data used in this analysis is at a more aggregated subbasin-level rather than at the field-level. To assign soil moisture to our field data, we intersect the soil moisture polygons with the map of field boundaries. This intersection, however, leads to duplication as field polygon intersects with multiple soil moisture polygons. To address this, we compute a weighted average of soil moisture values for each field, weighting by the area of overlap. Larger overlaps thus have a proportionally greater influence on the field-level soil moisture averages.

S1. E Creating Field-level Soil Quality Data

To construct soil quality variable, we obtain data on soil raster layers along with corresponding soil attribute information including available water capacity from Harmonized World Soil Database (Fischer, et al., 2008). The soil raster data is overlaid onto the cadastral shapefile containing field boundaries, and each field polygon is assigned the soil type covering the largest portion of its area. Soil attributes are then linked to fields via soil type identifiers. Because each soil type corresponds to multiple soil layers with varying properties, a direct merge leads to duplicate entries. To assign a single AWC value to a field polygon, we take an average across all layers. While a weighted average would be ideal, due to the lack of spatial information such an approach is not feasible.

Table 3 Descriptive Statistics

	Mean	**SD**	**Min**	**Max**
Parcel characteristics (2018-2022)				
Profits (dinars/ha)	62521	39310	0	157000
Spring Heat Stress Days (hours)	80	67	0	244
Spring Cold Stress Days (hours)	52	37	0	150
Winter Heat Stress Days (hours)	169	48	38.75	265
Winter Cold Stress Days (hours)	130	114	0	440
28-year Historical Spring Temperatures	18.9	0.3	17	20
Spring Soil Moisture (mm)	63	32.7	3	255
28-year Historical Soil Moisture	89	25	6	250

S2. Regression Results

S2. Table 1 Yield Weather Regression Model Results for Spring Crops

		Fixed Effects	
VARIABLES	**Maize**	**Soybean**	**Sunflower**
temp_neg2_to_1	0.004***	-0.002***	-0.00075***
	(0.0004)	(0.00054)	(0.00025)
temp_1_to_4	-0.001**	0.00052*	4.52e-05
	(0.0002)	(0.0003)	(0.00022)
temp_4_to_7	0.0005***	0.001***	0.00041**
	(0.0002)	(0.00024)	(0.00019)
temp_7_to_10	0.0017***	0.002***	0.00087***
	(0.0001)	(0.00015)	(0.00021)
temp_10_to_13	0.0022***	0.0048***	0.00076***
	(8.61e-05)	(0.00017)	(0.00015)
temp_13_to_16	0.0018***	0.00422***	0.00072***
	(0.00011)	(0.00015)	(0.00014)
temp_19_to_22	0.00014	0.00076***	0.00031**
	(0.00013)	(0.00018)	(0.00014)
temp_22_to_25	0.0006***	0.00424***	0.0013***
	(0.00015)	(0.0002)	(0.00014)
temp_25_to_28	0.0039***	0.005***	0.001***
	(0.00012)	(0.00017)	(0.00015)
temp_28_to_31	0.00022*	0.000971***	0.00016
	(0.00012)	(0.0002)	(0.00015)
temp_31_to_34	-0.000489***	-0.00066**	0.00039**
	(0.00014)	(0.00028)	(0.00019)
temp_34_to_37	-0.0024***	-0.0034***	0.00065***
	(0.0002)	(0.00018)	(0.00019)
temp_37_to_40	-3.10e-05	-0.0074***	0.0012***
	(0.0004)	(0.00035)	(0.00028)
early_season_soil	1.62e-05	-0.00036***	0.00046***
	(0.0001)	(0.00011)	(9.09e-05)
growing_soil	0.001***	0.0013***	0.00027**
	(0.00017)	(0.00021)	(0.00013)
harvesting_soil	-0.002***	-0.0027***	-0.00055***
	(0.00014)	(0.00021)	(0.00011)
Constant	-2.120***	-8.709***	-1.902***
	(0.253)	(0.502)	(0.550)
Observations	11,158,548	11,157,990	11,158,548
Number of id	1,859,758	1,859,665	1,859,758
R-squared	0.901	0.952	0.333

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

S2. Table 2 Yield Weather Regression Model Results for Winter Crops

	Fixed Effects	
VARIABLES	**Wheat**	**Rapeseed**
temp_neg8_to_neg5	0.00075***	0.0012***
	(5.60e-05)	(8.71e-05)
temp_neg5_to_neg2	0.00088***	0.0007***
	(7.35e-05)	(0.00016)
temp_neg2_to_1	0.0006***	0.0012***
	(6.16e-05)	(9.22e-05)
temp_1_to_4	0.00057***	0.00056***
	(5.62e-05)	(8.92e-05)
temp_4_to_7	0.00046***	0.00055***
	(6.90e-05)	(0.00011)
temp_7_to_10	0.00071***	0.00097***
	(4.09e-05)	(9.19e-05)
temp_10_to_13	0.0008***	0.00018
	(7.00e-05)	(0.00011)
temp_13_to_16	0.00036***	0.00047***
	(9.01e-05)	(0.00014)
temp_19_to_22	0.00041***	0.0007***
	(8.52e-05)	(0.00018)
temp_22_to_25	0.00063***	0.0018***
	(6.52e-05)	(0.00017)
temp_25_to_28	0.0015***	-0.00093***
	(0.000126)	(0.00024)
temp_28_to_31	-0.00068***	-0.0004***
	(5.90e-05)	(0.00013)
early_season_soil	-0.0013***	-0.0003**
	(7.72e-05)	(0.00012)
growing_soil	0.00052***	0.00052***
	(7.29e-05)	(0.00014)
harvesting_soil	0.00024***	4.44e-05
	(5.28e-05)	(9.98e-05)
Constant	-1.656***	-2.62***
	(0.332)	(0.587)
Observations	12,071,556	11,158,548
Number of id	2,011,926	1,859,758
R-squared	0.719	0.746

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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