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RESEARCH ARTICLE

Climate change-related lessons learned from a long-term field experiment with maize

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Abstract

Maize is the second most important cereal crop in European agriculture and a widely used raw material for feed, food, and energy production. Climate change studies over Europe predict a significant negative change in maize production. Finding appropriate and feasible adaptation strategies is a top priority for agriculture in the twenty-first century. Long-term agricultural experiments provide a useful resource for evaluating biological, biogeochemical, and environmental aspects of agricultural sustainability and for predicting future global changes. For the first time, we have been able to formulate a response to the question of which sowing date or hybrid choice strategies will prove beneficial in the future for the Pannonian region, based on sufficiently long experimental data. The objective of the study was to analyze a 30-year period of a multi-factorial long-term experiment at Martonvásár (Hungary) searching for traces of climate change as well as for favorable combinations of agro-management factors that can be used as adaptation options in the future. To analyze and extrapolate the data both in space and time, a multivariate statistical (response surface) model and a process-based crop simulation model were used. The results of the study yielded the following conclusions: (1) intensification of fertilization would not promote sustainable development in the region, (2) late hybrids have no perspective in the Pannonian climatic zone, and (3) earlier planting may become an effective adaptation option in the future. Our comprehensive methodology combines long-term historical weather and climate projection data with statistical and simulation models for the first time to provide agricultural stakeholders with more reliable adaptation strategies. It is essential to facilitate effective knowledge transfer to encourage farmers to adopt the proposed new practices. The collection of more detailed data for the entire Carpathian Basin will allow for the improvement of the models and projections.

Keywords Planting date · Genotype · Fertilization · Modeling · Adaptation strategies

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1 Introduction

Maize (*Zea mays* L.) is the second most important cereal crop in European agriculture (EC 2022a). In Hungary, it is the most significant crop in terms of harvested area (KSH 2022). Maize is widely used for feed, food, and energy production (EC 2022b). All these uses are expected to face significant impacts from climate change.

Studies on climate change in Europe consistently show rising temperatures. Precipitation patterns are also changing, with increases in northern Europe and decreases in parts of Southern and Eastern Europe (Olesen et al. 2011). In Hungary, significant warming is expected within the Carpathian Basin. The largest temperature rise is projected for summer, accompanied by a major reduction in summer precipitation (Pongrácz et al. 2011). However, the latest climate projections show considerable uncertainty (see Fig. 5).

Many modeling studies, at both global and regional scales, have explored how climate change may affect maize production. They have also assessed the potential of agro-management options like irrigation, fertilization, planting dates, and hybrid selection. Webber et al. (2018) reported that drought losses for maize in Europe are likely to increase. Elevated CO_2 will not offset these losses. Parent et al. (2018) found that maize yields in Europe could increase by 4–7% if hybrids and sowing dates are optimized locally. Adaptation measures have been shown to reduce the yield gap between northern and southern Europe. This could lead to higher maize production if farmers adopt best practices. Moore and Lobell (2014) highlighted maize's high adaptation potential to climate change in Europe. Agricultural profits may slightly increase with adaptation but could fall significantly without it. Large-scale modelling studies employ mechanistic models to extrapolate and interpolate observed data, frequently encountering a loss of local relevance. This underscores the significance of emphasizing local data and expertise in refining global crop models to generate more precise and region-specific predictions (Silva and Giller 2020; Kephe et al. 2021).

Local studies provide detailed insights into expected changes. Mereu et al. (2021) showed that maize yields in Italy will face consistent reductions from north to south. Bassu et al. (2021) predicted that by 2060, maize yields in the Mediterranean region could decrease by 14–17%. This loss may only be partially mitigated by adjusting genotypes and sowing dates. In northern Europe, warmer conditions may allow maize to expand northward. Eckersten et al. (2012) found that silage maize could maintain adequate quality annually in southern Sweden by the end of the century. However, in central Sweden (60 °N), about 30% of the years would fail even for the earliest cultivars. Žydelis et al. (2021) predicted maize yield increases of 200–300 kg ha^{-1} per decade in South Scandinavia and the Baltic region. In southern Romania, Cuculeanu et al. (1999) found maize to have negative responses to climate change. Effective strategies include irrigation, longer-maturing hybrids, later sowing, and increased nitrogen use. Parker et al. (2017) noted that earlier planting in Germany may raise yields but adds management costs and risks. Buhiniček et al. (2021) argued that early hybrids may not be the best choice for Southeast Europe. In Hungary, Fodor et al. (2014) estimated yield losses of up to 2000 kg ha^{-1} y^{-1} by 2100 from the current average yield of 6000 kg ha^{-1}. However, sustainable management could reverse these trends (Marton et al. 2020).

Adaptation strategies vary by region. They depend on local conditions and opportunities. This highlights the importance of local field experiments for calibrating and validating models. Models must be tested before addressing scientific or practical problems (Kersebaum et al. 2015; Ginaldi et al. 2016; Choruma et al. 2019; Liang et al. 2018). Multi-factorial experiments examine the effects of two or more factors, such as variety selection (V), fertilization (F), irrigation (IR), planting date (P), and plant density (PD). Russelle et al. (1987) identified the optimal F×P combinations for irrigated maize in Nebraska over three years. Tsimba et al. (2013) studied V×P interactions for maize in New Zealand and concluded that delayed planting is not ideal. Bassu et al. (2021) analyzed V×P×PD interactions in Italy under optimum management over 3 years. They found early sowing to have a larger yield effect than cultivar selection. However, short trials like these may not capture long-term climate trends. Weather over 2–5 years may not represent local climate variability or climate change-induced trends.

Although long-term agricultural experiments (LTEs) have numerous constraints and weaknesses (e.g., change of genotypes) they are the only way to identify long-term trends (Berti et al. 2016) as well as robust, site-specific features of the interactions between the investigated factors. By definition, these experiments are carried out for at least 20 consecutive years and study crop and/or livestock production, nutrient cycling, and environmental impacts of agriculture (Grosse et al. 2020; Macholdt et al. 2020; Li et al. 2023; Pereyra-Goday et al. 2024). They provide a useful resource for evaluating biological, biogeochemical, and environmental dimensions of agricultural sustainability and for predicting future global changes (Rasmussen et al. 1998; Reckling et al. 2018). These experiments are valuable for spatially differentiated data analyses and reuse of data in modelling studies for validating model capability and performance (Grosse et al. 2020; Rasmussen et al. 1998). LTEs are long enough to detect the effects of climate change on the factors investigated in the experiments (Donmez et al. 2023) yet, they cannot give us final answers on the expected changes in climate in the future - and their implications on maize crop performance. Recent decades have seen a shift in LTE focus from specific practices to combinations of practices and their interactions. This more holistic approach supports climate-smart agroecosystem management (Blanchy et al. 2024).

Although our study is geographically limited, it is a good representation of Hungary and its wider surroundings, the Carpathian Basin, in terms of maize production. The Carpathian Basin, or the Pannonian climatic zone, is dominant on a European scale and it covers several countries. The amount of maize produced in this region exceeds that of France, the largest maize producer in the EU. The results of climate change models indicate that the Pannonian basin will experience significant ramifications across multiple sectors and the ecosystem, positioning it as a region of Europe that will be particularly vulnerable to the consequences of climate change. This area is projected to have the highest number of severely affected sectors in Europe (Lukić et al. 2019). As the quality of available methods, soil data, and climate projections improves, it will be possible to refine calculations and forecasts of productivity for this crucial region. The most recent study of this region was carried out more than 10 years ago. Consequently, there is a significant need for updated research. In recent years, the 100-m resolution soil map of Hungary has been produced with the support of artificial intelligence, the latest IPCC climate projections have become available, and the database of the Martonvásár long-term field experiments has been completed. However, key questions remain. How is the region's productivity changing? If trends are negative, what can reverse or mitigate them?

The objective of the current study is to analyze a 30-year period of a multi-factorial (Variety × Fertilization × Planting date; V×F×P) LTE at Martonvásár, Hungary (Fig. 1) searching for the traces of climate change in the yield trends as well as for favorable combinations of agro-management factors that can be used as adaptation options in the future.

2 Material and methods

2.1 Soil and climatic characteristics of the experiment area

The field trial was carried out on the experimental farm of the Centre for Agricultural Research, Martonvásár, Central Hungary (N 47°19′, E 18°47′, 110 m asl, see embedded map in Fig. 8.). The soil is classified by FAO-WRB (IUSS Working Group 2015) as a Haplic Chernozem (34% sand, 42% silt and 24% clay in the 0–25 cm layer), with average pH_{H2O} of 7.59, 1.84% $CaCO_3$, 3.39% Soil Organic Matter, and 1799/374/429 mg kg^{-1} total N/P/K content. Based on the water retention curve measured in the laboratory, the saturated water capacity, the field capacity, and the water content at wilting point are 0.476, 0.322, and 0.134 cm^3 cm^{-3}, respectively. In order to gain insight into the spatial scalability of the results that will be presented subsequently,

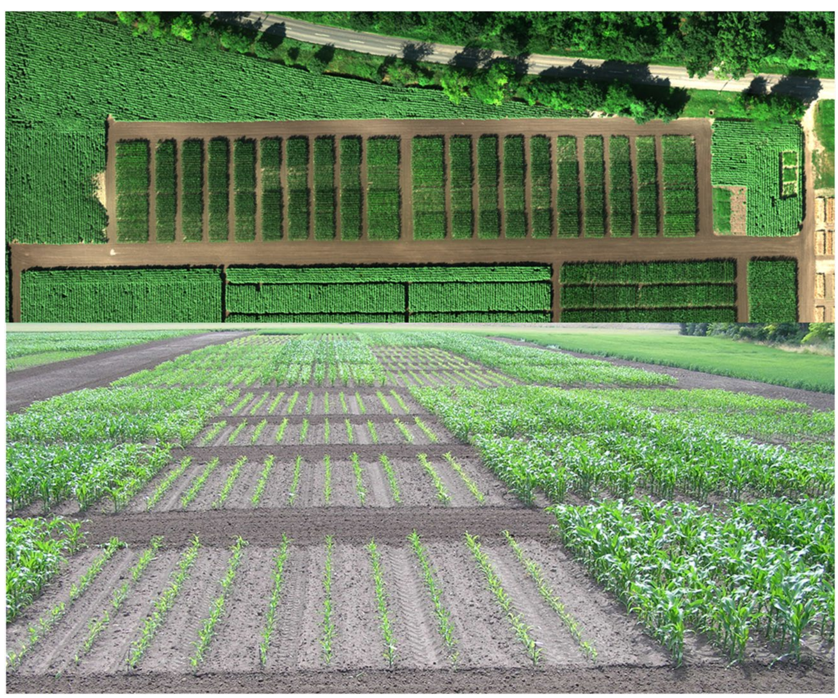

Fig. 1 Aerial photo of the long-term field experiment at Martonvásár (24/06/2024) and its immediate surroundings. The multi-factorial experiment was initiated in 1991 with the aim of investigating the long-term effects of combinations of variety, fertilization, and planting date treatments. Aerial photo by György Balassa, ground photo by Gabriella Málovics.

an investigation was conducted into the prevalence of the soil type of the Martonvásár area. According to the global soil map of the World Reference Base for Soil Resources (IUSS Working Group 2015) Chernozems cover 20.7% (1.17 million hectares) and 15.6% (2.39 million hectares) of the arable area in Hungary and in the Carpathian Basis, respectively. In Hungary, Chernozems account for the largest share of arable land, ahead of Vertisols and Gleysols.

Long-term, annual meteorological data for the area, recorded at an on-site station, are shown in Fig. 2. For each year, precipitation sum (Psum), mean temperature (Tmean), the number of hot days when the daily maximum temperature is over 30 °C (nrHotD), the number of days with precipitation (nrPD) when precipitation exceeds 0.1 mm, vapor pressure deficit (VPD) and total reference evapotranspiration ($refET_0$, defined by Allen et al. 1998) are plotted.

In the Supplementary Material, these indicators are presented for the vegetation period, the flowering period and also for the grain filling period (Fig. SM1). The significance of the trend in climatic characteristics was tested using *t*-tests, and t-test conditions (normality of the residuals and absence of auto-correlation) were tested using Jarque-Bera and Durbin-Watson tests, respectively, with the help of the *statsmodels 0.13.5* Python package. The required conditions for applicability were met for all the characteristics examined.

Trends of the above climatic indicators were investigated for the whole study area to see how the changes at Martonvásár are representative of trends across the region. For this purpose, the FORESEE database (Kern et al. 2024) was used. Its 10 × 10 km resolution grid covers the area of Hungary with 1014 cells containing observation based, spatially interpolated, daily weather data.

We also examined the correlation between yields in Martonvásár and the national average at 5% significance level. The country-level yield data were obtained from the open-access database of the Hungarian Statistical Office.

2.2 Experimental design

The experiment involves three factors: four planting dates (P), five fertilization doses (F), and five varieties (V) in every single year. The choice of varieties changed over the years, reflecting breeding progress but in each year (Y) five different varieties were sown from the early, medium and late maturity groups. The list of varieties used in the trial is shown in Table 1. FAO number is a characteristic of maize maturity groups (Jugenheimer 1958): the lower the number, the fewer heat units that are required to reach grain maturity. According to their FAO numbers, early (FAO 290–320) medium (FAO 330–420) and late (FAO 430–550) varieties were sown in each year. In the five fertilization treatments (F=1 to 5) 0, 60, 120, 180, and 240 kg ha^{-1} N was applied annually, two weeks before the first planting date. Planting date treatments are described in Table 2.

We aimed to have a hybrid from each of the three maturity groups in the trial every year. Although there were no hybrids included in the trial every year, the official crop investigation and certification system in Hungary guarantees that the expected yield of the new registered hybrids included in the trial will be at least as high as that of the older cultivars.

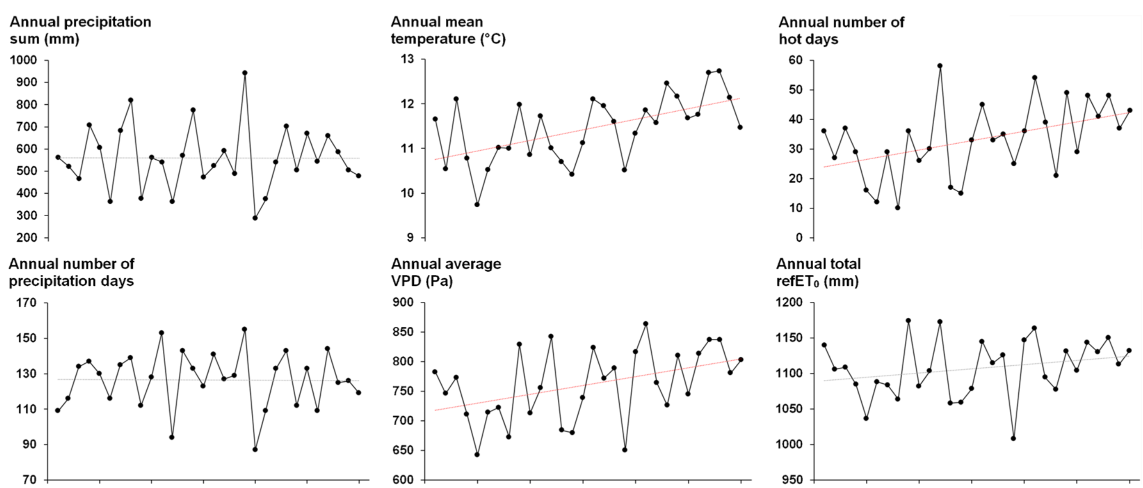

Fig. 2 Weather conditions of the experimental site between 1992 and 2021, Martonvásár, Hungary. Data were collected by an onsite meteorological station maintained by the Hungarian Meteorological Service. By definition, a day is hot if the maximum temperature exceeds 30 °C. VPD and $refET_0$ denote vapor pressure deficit and reference evapotranspiration, respectively. Dotted (red) lines indicate (significant) linear trends.

Table 1 List of varieties used in the experiment. The Years column indicates the period of years when the varieties were used in the experiment.

Variety	FAO number	Years
Mv Tc 1287	320	1992–1994
Mara	290	1995–1998
Mara	290	1999–2000
Mv 272	300	1999–2001
Mv 277	300	2002–2021
Norma	370	1992–1913
Dáma	330	2001–2003
Hunor	350	2004–2021
Furio	390	1992–1994
Mv 355	400	1995–2020
Tarján	380	2014–2021
DK 524	530	1992–1994
Maya	430	1995–1997
Botond	420	1998
DK 608	550	1992–1993
Mv 1514	540	1994
Mv 484	480	1995–1996
Maraton	450	1997–2008
Miranda	460	2009–2015
Danietta	500	2016–2020
Mv 352	500	2021

Table 2 Planting date treatments used in the experiment. DOY denotes the day of the year.

Planting date (P)	Planting dates (DOY): min / median / max
1	94 / 103 / 116
2	104 / 113 / 122
3	115 / 123 / 131
4	127 / 134 / 141

In order to conserve soil quality, byproducts were left in the plots and incorporated into the soil after harvest in each year. The soil organic carbon (SOC) content is a frequently used indicator of soil quality. SOC was measured in 1989, before the experiment began: 20 holes were drilled. In 2018 (one hole from each treatment and replicate) a total of 80 holes were drilled. Samples were taken from the holes from three depths (0–30, 30–60, and 60–90 cm) and the SOC content of the samples was measured in an accredited laboratory. To determine if there was a significant change in SOC and, by extension, soil quality, we conducted the Mann-Whitney *U*-tests and Permutation tests (Good 2005).

The experiment has four replications. Planting date was the main plot factor of the trial and was laid out according to a Latin square design with four superrows and four supercolumns, denoted by factors SR and SC, respectively (Fig. 3). Each superrow was divided into five longrows (LR), to which the five fertilizer levels were allocated. Furthermore, each main plot was divided into five columns (CL) to accommodate the five varieties tested in each year. The observational unit is the subplot (SP), located at the longrow×column intersections.

2.3 Statistical analysis

In the treatment factors planting dates, fertilization doses can be treated as both qualitative (P, F) and quantitative (D, N) characteristics. Additionally, the factor variety (V) and year (Y) can be explored by its quantitative FAO classification (M) and time trend (T), respectively. For the latter two, we do not expect that quantification can explore all variation seen within the factors. However, the aim of the current analysis is to explore the quantitative nature of all four factors. A general overview on model development is shown in Fig. 4. Two final models were developed: One model with a single response surface curve fitted across years and another model fitting separate response surface curves for good and bad years, with below-average and above-average yields, respectively.

2.3.1 Model development for single surface model

Block model The statistical model used for analysis is developed here by first considering a single year and then extending to multiple years. To represent the field layout and allocation of treatments to experimental units, the following block model (Piepho et al. 2003) is used for a single year, using the block factors defined before:

$$\mathrm{SR} + \mathrm{SC} + \mathrm{SR.SC} + \mathrm{SR.LR} + \mathrm{SR.SC.CL} + \mathrm{SR.SC.LR.CL} \tag{1}$$

Here, SR.SC corresponds to main plots, and SR.SC.LR.CL corresponds to subplots. Hence, all six block factors shown in Fig. 3 are represented. All design effects in this block model are modelled as random. We extend the model to multiple year by extending each effect with the factor year (Y):

$$\begin{aligned}&\mathrm{SR.Y} + \mathrm{SC.Y} + \mathrm{SR.SC.Y} + \mathrm{SR.LR.Y}\\&\quad + \mathrm{SR.SC.CL.Y} + \mathrm{SR.SC.LR.CL.Y}\end{aligned} \tag{2}$$

Year is denoted as the repeated factor (Piepho et al. 2004) because it indexes repeated observations on the same design unit. The design unit itself is identified by the level of the effect in (1) that is extended by factor Y in (2). For example, main plots are identified by levels of the effect SR.SC, and all observations on the same main

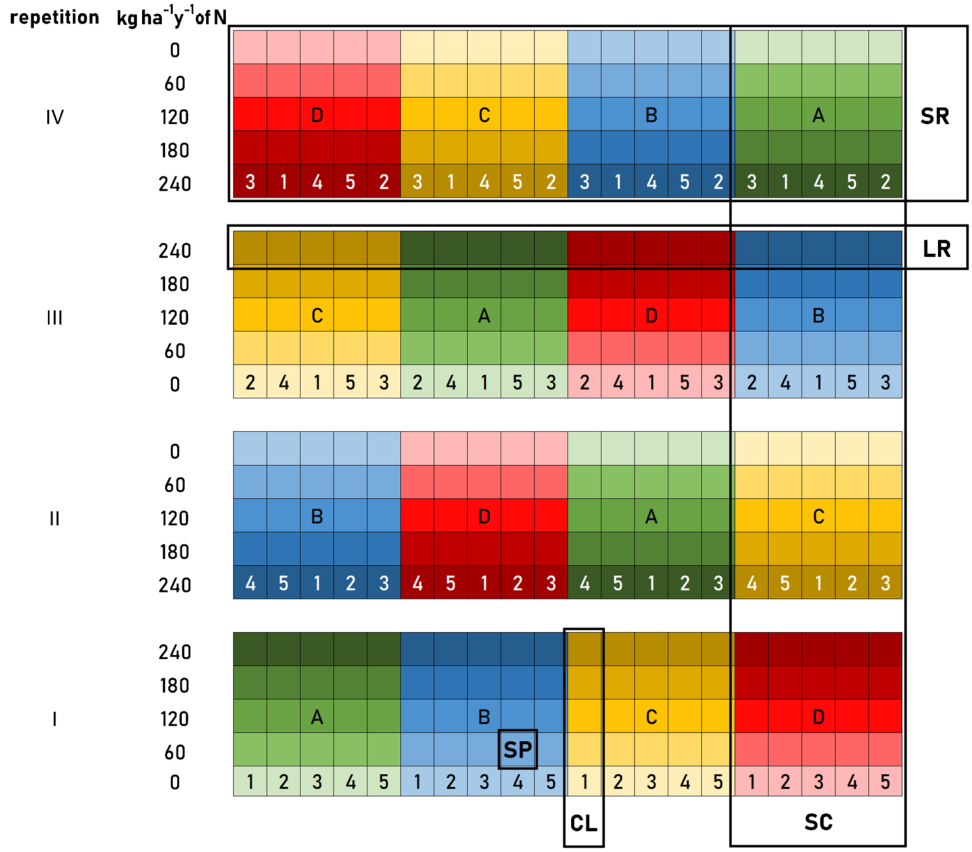

Fig. 3 Layout of the experiment. The green, blue, yellow, and red fields denote different planting dates. The planned dates after 2010: A—first decade of April, B—second decade of April, C—third decade of April, D—first decade of May (10 days later than before 2010). Numbers in the colored fields (1 to 5) denote the tested varieties within a year (varieties within a year were sorted according to FAO numbers). The color shades denote different N fertilization levels (darker shades for higher levels, from 0 to 240 kg ha^{-1} y^{-1} nitrogen). Latin numbers (I to IV) denote replicates. One representative of superrows, supercolumns, longrows, columns, and subplots is denoted with SR, SC, LR, CL, and SP rectangles, respectively.

plot are assumed to be serially correlated. Here, we use the first-order autoregressive AR(1) model with all design effects in (2) except for the subplots where we additionally allow for heterogeneous variances (ARH(1)).

Treatment model The treatment model is developed using the P, F, and V factors included in the experiment. The basic treatment model for a single year is as follows:

$$V \times F \times P = V + F + P + V.F + V.P + F.P + V.F.P \quad (3)$$

This model is modified to account for the random factor Y by adding a random main effect for Y and also adding all effects in (3) crossed with Y as random. Hence, the extended model is as follows:

$$V \times F \times P \times Y = V + F + P + V.F + V.P + F.P + V.F.P + Y + V.Y + F.Y + P.Y + V.F.Y + V.P.Y + F.P.Y + V.F.P.Y \quad (4)$$

where random effects are listed after a colon. The full model is obtained by combining models (2) and (4).

Response surface regression Models so far treated P, V, F, and Y as qualitative factors. However, P can be quantified by day of year (D) and F by the amount of nitrogen (N). Additionally, V can be quantified by the FAO number M and Y can be quantified by the continuous variable T for calendar year. In the latter two cases, we do not expect that all differences in V and Y can be covered by M and T, respectively. Furthermore, note that preliminary inspection revealed that N shows a response with diminishing returns reaching a plateau and then dropping only slowly with further increasing N. A quadratic model in N may not represent this well. Hence, we experimented with different powers of N and decided to replace N with $N^{1/2}$. To simplify the presentation, we replaced N values by their square root but kept the symbol N to represent the factor. We fitted a second-order response surface model with all four variables D, N, M, and T. Such a model is satisfying if there are no serious deviations from the response surface. To check this assumption, we first fitted a second-order response surface regression to single-year data using D, M, and N as quantitative regressor variables. In that first step, we fitted the treatment model given by the following:

$$D + D.D + M + M.M + N + N.N + D.M + D.N + M.N + V.F.P \quad (5)$$

separately for each year (Y) and assessed the lack of fit using the fixed effect V.F.P. In addition, the model comprised all random design effects in Eq. (1). The model fit was satisfactory (see Supplementary Material), hence we considered an extension of the second-order response surface model by

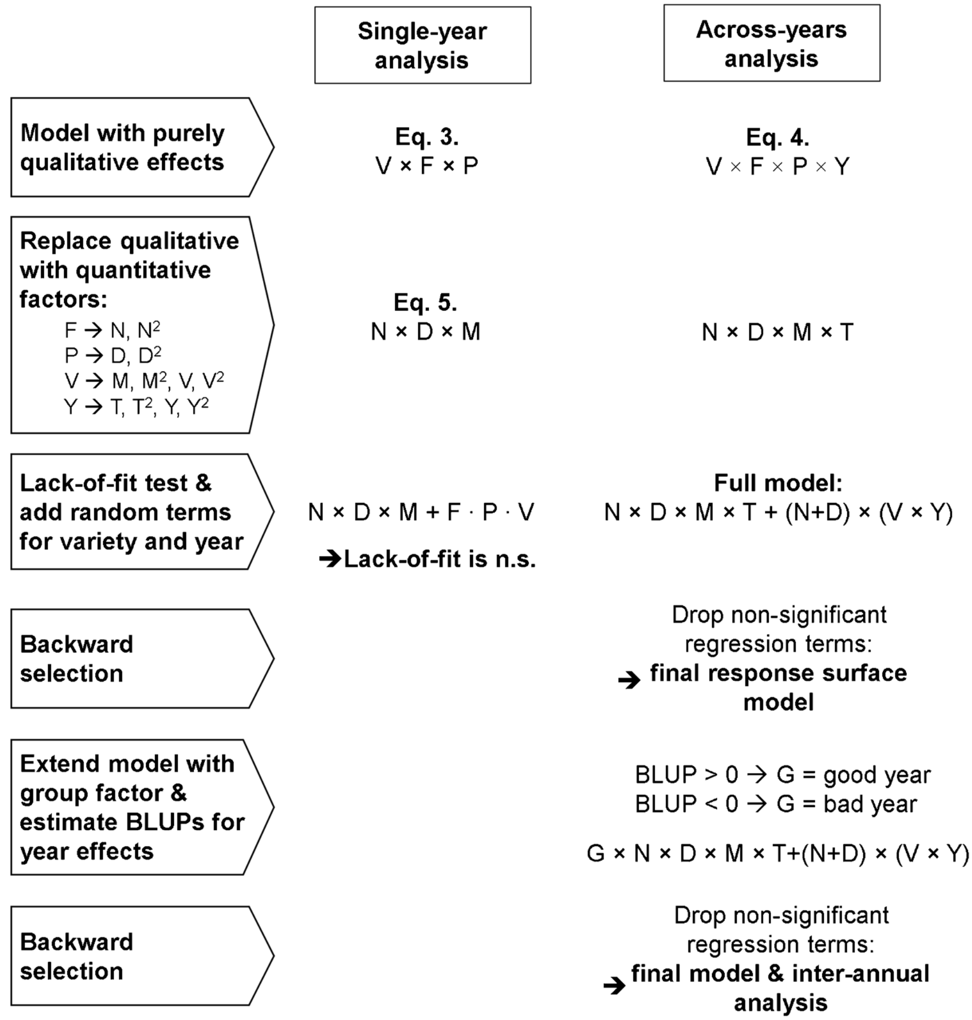

Fig. 4 The general analysis approach leading to two final models. Note that block effects and specific variance-covariance structures are not shown here to simplify presentation. The terms F, P, V, and Y represent qualitative factors fertilizer dose, planting date, variety, and year. The terms N, D, M, and T represent quantitative variables fertilizer dose, planting time, FAO number, and time trend. BLUP is the abbreviation of best linear unbiased prediction.

inclusion of the continuous factor T for the calendar year. In this case, no lack-of-fit test (test of V.P.F.Y) was performed for the across-year analysis as we assumed that the trend will not explain years completely and there is for sure year-by-year variation that will be captured by the random effects involving Y in Eq. (4). Additionally, both factors Y and V were now assumed as random, while quantitative variables M and T were taken as fixed. The full model therefore included the second-order response surface regression on variables M, D, N, and T as fixed effects, all effects from (4) including either V or Y as random effects, and all effects of (2) as random effects.

After fitting the response surface regression for all four quantitative variables, the fixed effects were subsequently pruned by discarding non-significant effects, observing the marginality principle. Thus, we started by inspecting the highest-order interaction and removed it if it was not significant (at $\alpha = 0.05$), in which case we moved on to the nearest lower-order interactions to proceed with the next tests, etc. A summary of the covariates used in the regression analyses is presented in Table SM1.

2.3.2 Model development to fit separate response surface curves for good and bad years

For the final model developed above we inspected best linear unbiased predictions (BLUPs) for the random deviations of Y from trend T. Based on these BLUPs we fitted a separate response surface regression for (i) years with positive (=good years) and negative BLUP (=bad years). Again, fixed effects crossed with group were selected via backward selection.

The fitted models are reported as contour plots for two of the four variables (two out of the four variables D, M, N, and T), fixing the other two at specific values. For analysis, we centered M at 350, T at 2010 and D at 120. This linear shift is intended to numerically stabilize the regression analysis. It does not affect slope estimates but does shift the intercept. The fitted values are not affected.

The statistical analysis was performed using ASReml 4.2 standalone for analysis and PROC RSREG in SAS for graphics. For those interested in further details on the method used, we recommend the following publications: Box and Draper 2007; Piepho and Edmondson 2018.

Note, that in exploring possible temporal trends the effect of a total of 58 annual and monthly environmental factors (see examples in Fig. SM1) was also investigated. These factors were included as covariates in the single response surface model. As detailed in the Discussion section, weather-related covariates (Table SM2.) were not used in the final model, since year factor (Y) has been shown to be a reasonably good integrator that aggregates the impact of weather factors and their variations with sufficient statistical confidence.

Though there are many reasons why results from a LTE can be useful for providing useful information on promising measures to adapt to a changing climate; yet, there are also limitations in view of various aspects: (i) shifts in future seasonality (i.e., shifts in rainfall patterns but also frost risk patterns, etc.) that are part of climate change projections, need to be considered when deriving potentially promising adaptation options from experiments conducted historical (past) weather conditions; (ii) effects of elevated atmospheric CO_2 concentration: although these have to be considered most for crops of the C3 photosynthetic type (like wheat or barley) (e.g., Lobell and Gourdji 2012; Rötter and van de Geijn 1999) elevated CO_2 also has beneficial effects on C4 crops like maize, in particular in improving their water use efficiency under drought conditions (e.g., Durand et al. 2018) as is also the case for C3 crops (O'Leary et al. 2015). To overcome these shortcomings crop growth simulation was used for extrapolating the patterns detected in the LTE results for the future. Crop modeling has the potential to help us understand the relative influence of environmental factors (such as climate and soil) and genotype and management on the outcomes of long-term experiments. For example, Dobermann et al. (2000) explored this in their research.

2.4 Crop model simulations

The potential of the choice of planting date as a mitigation option was examined in depth using the Biome-BGCMuSo biogeochemical model. The Biome-BGCMuSo model is a general-purpose, process-based model that simulates the full carbon, nitrogen, and water budget of terrestrial ecosystems (Fodor et al. 2021; Hidy et al. 2022). Biome-BGCMuSo is a branch of the well-known Biome-BGC model, which was first developed by Running and Hunt (1993). Over time, the model has undergone significant improvements and expansions. The enhancements addressed key areas such as soil processes, management options, and disturbance effects on plant physiology. Many other processes were also refined (Hidy et al. 2016). The model was further improved to simulate the effects of stress factors, including drought, nitrogen deficiency, and heat stress. For cropland simulations, the model requires meteorological, soil, and crop input data, as well as detailed management information. This includes the timing and amount of fertilizer, planting and harvest dates, and residue management. Locally measured meteorological and soil data were used as inputs. Observed plant data, including yield, maximum leaf area index (LAI_{max}), flowering date, and harvest index, were used for model calibration. Calibration was performed using the Conditional Interval Reduction Method (CIRM) (Hollós et al. 2022). This machine-learning approach uses decision tree-based white box approximations. It calibrates parameters such as the length of vegetative and reproductive periods, specific leaf area, and biomass partitioning into roots, stems, leaves, and kernels. CIRM effectively uses limited data as constraints to ensure realistic simulations. For example, it ensures that LAI_{max} stays within observed intervals. Yield data was used to minimize the difference between the observation and the simulation during calibration. The rest of the observations (Table 3) were used as constraints to ensure realistic simulations with the calibrated model parameters. Calibration only included treatments meeting the following conditions: nitrogen level between 120 and 180 kg/ha, hybrid FAO number between 300 and 400, and planting dates between day of year (DOY) 105 and 120. These conditions align with typical practices of Hungarian farmers during the study period.

With a minor change, we applied the method suggested by Ojeda et al. (2018) to assess model performance both in

Table 3 Range of observed plant phenotypic data supporting crop model calibration used as constraints in the CIRM method. Flowering dates are given in DOY.

Observed feature	Minimum	Maximum	Observation period
Flowering date	176	192	2001–2022
Maximum of leaf area index	2.9	4.2	2001–2004 and 2017–2022
Harvest index	0.48	0.55	2005–2017

calibration and validation. The following statistical indicators were used: concordance correlation coefficient (CCC) defined by Lin (1989), mean absolute error (MAE) defined, e.g., in Willmott and Matsuura (2005) and mean signed error (MSE, also known as bias) which is also defined in Lin (1989) We decided to use MAE instead of root mean square error as the former has some advantages over the latter: MAE is a more natural and unambiguous measure of average error (Willmott and Matsuura 2005).

During validation, simulations were carried out for the 2001–2020 period for a 10 × 10 km resolution grid covering the area of Hungary with 1014 cells. For each cell, soil and weather data were retrieved from the DOSoReMI (Pásztor et al. 2020) and the FORESEE (Kern et al. 2024) databases, respectively. For all simulations 150 kg/ha/year N fertilizer level and April 25 (DOY = 115) as planting date were used uniformly. Simulated yields were aggregated on NUTS-3 (county) level (EuroStat 2024) and compared to the observed yield data retrieved from the database of the Hungarian Statistical Office.

For future simulations, observed weather data was replaced with projections (Fig. 5) from five Global and Regional Climate Model (GCM-RCM) combinations under the RCP4.5 and RCP8.5 scenarios (van Vuuren et al. 2011). Simulations were conducted for two future periods, 2041–2060 and 2081–2100. This resulted in 20 future simulations for each grid cell: 10 using current agro-management practices (BAU – Business As Usual) and 10 with planting dates shifted three weeks earlier (3WEP). Results from BAU and 3WEP were aggregated separately and compared across the baseline period (2001–2020) and future periods using color-coded maps. Simulations concerning the future also take into account the increase in atmospheric CO_2 concentrations, as the process-based crop model (Biome-BGCMuSo, Fodor et al. 2021) employed in this study considers the impact of elevated CO_2 concentrations on photosynthesis and evaporation.

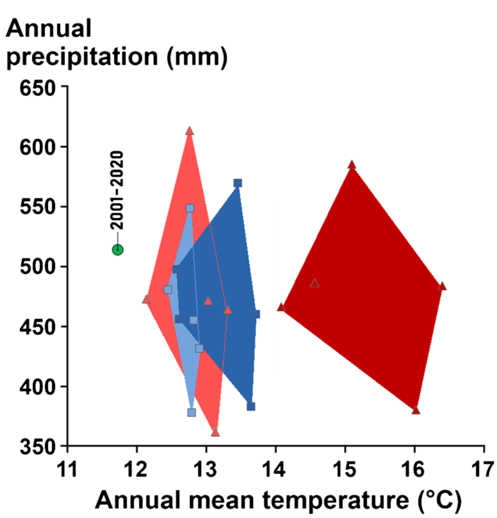

Fig. 5 Key characteristics of the 10 climate projections used in the study compared to the baseline (2001–2020) period. The 5 GCM-RCM model combinations that were driven by the RCP4.5 (squares) and RCP8.5 (triangles) scenarios were the following: CNRM-ALADIN53; HadGEM2-CCLM; NCC-HIRHAM5; HadGEM2-RACMO22E; MPI-CCLM. Light and dark colors represent the 2041–2060 and 2081–2100 periods, respectively.

3 Result and discussion

3.1 Trends of climatic indicators and yields

At the long-term experiment site, significant trends were found for the temperature-related (Tmean and nrHotD) indicators as well as for Vapor Pressure Deficit. The expected number of hot days in the flowering period more than doubled and the mean temperature rose by more than 2 °C during the 30 years of the study period (Fig. SM1). For all indicators for which a significant trend was identified at the Martonvásár site, the same trends were observed across the entire region, and those were significant for a considerable proportion of the area: 100%, 64.1%, and 90.8% in case of Tmean, nrHotD, and VPD, respectively. In light of this, it can be reasonably concluded that the climatic changes responsible for the observed effects at Martonvásár are likely to have a similar impact in the whole region under study. The subsequent modelling results serve to corroborate this conclusion (see Section 3.6). There were no significant changes in the amount or distribution of precipitation for the whole year or for shorter periods within the year. Heat stress and atmospheric drought appear to be responsible for the adverse changes in yield levels.

The correlation coefficient between the local (Martonvásár) and the national average yields for the 30-year period under study is 0.77 ($\alpha = 0.05$). This value indicates a strong and statistically significant relationship between the yields of two different spatial scales. Given the robust correlation observed, the yield results of the long-term experiment appear to serve as a reliable indicator of yields in the region.

3.2 Single response surface model

Our main fitted model, obtained after model selection, is reported in Table 4. Quadratic terms are significant for factors N, M, and D, and the regression coefficients are negative. For time, only linear terms are significant, including the interactions M.T and D.T. The presence of these interactions means that the optimal sowing dates (D) as well as the optimal maturity class (M) change over time.

Table 4 Selected single response surface regression model for yield (Mg ha^{-1}) with parameter estimates, standard errors and t-tests. The terms N, D, M, and T represent quantitative variables fertilizer dose, planting day, FAO classification, and time trend.

Effect§	Estimate	Standard error	t-value	p-value
Intercept	6031.13	446.14	13.52	<0.0001
N	435.61	38.1982	11.40	<0.0001
N.N	−17.8776	2.4380	−7.33	<0.0001
D	−23.4818	5.6154	−4.18	<0.0001
D.D	−1.7090	0.3883	−4.40	<0.0001
M	8.8217	3.7738	2.34	0.0194
M.M	−0.06767	0.02784	−2.43	0.0151
T	−47.0981	40.8646	−1.15	0.2491
N.D	−2.2058	0.2406	−9.17	<0.0001
D.T	−1.1054	0.5460	−2.02	0.0429
M.T	−0.3239	0.1420	−2.28	0.0226

The terms N, D, M, and T represent the square root of fertilizer dose (kg ha^{-1}), planting time (DOY), FAO number and time trend. D, M, and T were centered at 120, 350, and 2010, respectively

3.3 Time series analysis

The first and most important result of the developed model is that it predicts a clear decline in yield levels irrespective of the nutrition level, the maturity group and of the planting date (Fig. 6). Even with adequate nutrient supply, hybrid and planting date selection yield levels of over 10 tons per hectare in the early 1990s have fallen well below 9 tons in three decades (Fig. SM2). The shape of the iso-lines shows that the yield levels of late varieties decline at a much more intense rate than that of the early hybrids (Fig. 6b): compare the change of around 3 Mg ha^{-1} for the late varieties (FAO > 500) with the practically constant yield levels for the early hybrids (FAO < 300), over three decades.

The data analysis resulted in the following temporal trends for the optimum nitrogen fertilization level (N), the optimum FAO number (M), and for the optimum planting date (D).

$$N_{opt}(D) = (12.1831 - 0.0617 \bullet (D - 120))^2 \tag{6}$$

$$M_{opt}(T) = -2.3932 \bullet (T - 2010) + 415.18 \tag{7}$$

$$D_{opt}(T, N) = -0.3234 \bullet (T - 2010) - 0.6453 \bullet N^{0.5} + 113.13 \tag{8}$$

The optimum level of N fertilization did not change significantly over time (Eq. 6). Its value has stagnated at around 177 and 144 kg ha^{-1} (Fig. 6a) for early and late sowing, respectively (Fig. SM2). This observation simply reflects the fact that higher yield productions require more nitrogen inputs. It is important to note that this fertilization level corresponds with the highest average yield not with the maximum income. The maximum income-based N fertilization optimum is closer to 120 kg ha^{-1} as above this level the yield achieved increases only slightly with increasing fertilizer rates (Fig. SM2). For a given planting date, the time invariant optimal level of nutrient supply corresponds with smaller and smaller yields.

Regarding variety selection, the optimal FAO number, providing the highest possible yield on average, is clearly decreasing with time (Fig. 6b, Eq. 7). Before 2000, hybrids with FAO number over 450 gave the highest yields, irrespective of the nutrition level and the planting date (Fig. SM3). Today, the medium-early maturity group hybrids (FAO number less than 400) provide the highest possible yields.

A similar clear trend could be observed in the optimum sowing date during the study period (Fig. 6c, Eq. 8). Irrespective of hybrid selection the optimum sowing date shifted 10 days earlier during the 3 decades of the experiment. The benefit of earlier sowing dates is also reflected in the level of N fertilization resulting in a 4 days of average difference between the extensive (60 kg N ha^{-1} y^{-1}) and the intensive

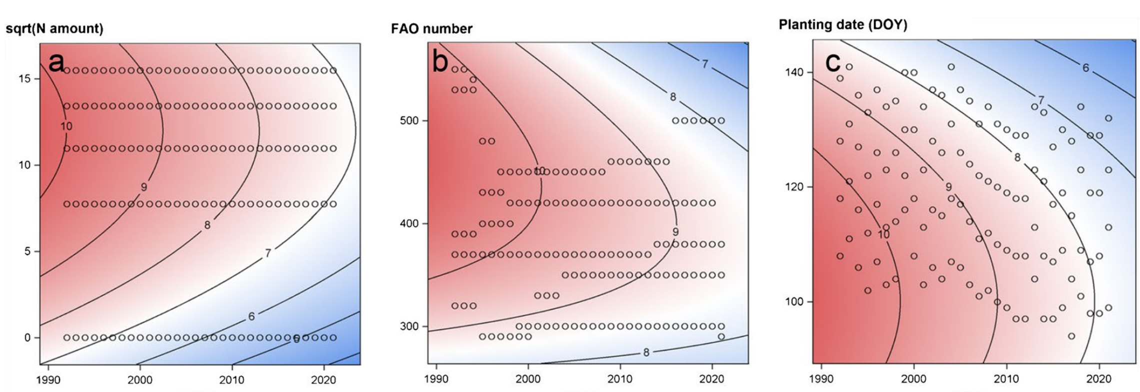

Fig. 6 Contour plots of the model results describing temporal changes in the effect of the investigated factors. **a** Planting date = 102 and FAO number = 500; **b** Planting date = 102 and N amount = 180 kg ha^{-1}y^{-1}; **c** FAO number = 500 and N amount = 180 kg ha^{-1} y^{-1}.

(180 kg N ha^{-1} y^{-1}) nutrition regimes (Fig. SM4). Earlier sowing obviously entails a higher yield potential and thus higher N application is required to realize that potential.

3.4 Analysis of inter-annual differences

Regardless of the year type (good or bad) and the fertilization level, hybrids of the same maturity group produce the maximum yield. Hybrids with around 420 FAO number comprise the optimal maturity group (Fig. SM5). Important to note, that this is an average for the 30 years. As it was shown earlier that the FAO number of hybrids with the highest yields clearly decreased over the observation period.

In bad years, the optimal planting date is more than two weeks earlier than in the high-yielding years (Fig. SM5). The difference is more pronounced in stands fertilized intensively (DOY = 82 vs DOY = 108) than in stands fertilized extensively (DOY = 89 vs DOY = 111). The optimal sowing date does not depend at all on variety selection. There is a month difference between the earliest optimum planting date, corresponding to intensively fertilized hybrids in bad years, and the latest planting date optimum (extensively fertilized hybrids in good years). The flatness of the isolines in the direction of the planting date axis in sub-optimal years shows that the further away we are from choosing the right hybrid (Fig. SM5), the less important the sowing time. According to the contour plots the planting date-related results could be summarized as follows: (1) the worse the year the earlier the optimum planting date (Fig. SM5); (2) the earlier the planting date the higher the optimum N fertilization level as more fertilizer is needed to achieve the expected higher yields (Fig. SM6); (3) the higher the N fertilization level the more sensitive the yield level to planting date especially in suboptimal years (Fig. SM6).

In bad (under average yield) years, considerably less nitrogen is needed for maximum yields. Irrespective of hybrid or sowing date selection the adequate level of N fertilization is around 50 kg ha^{-1} less in sub-optimal years (210 vs 159 kg ha^{-1}) corresponding to a slightly over 3 Mg ha^{-1} yield difference between the two types of years (Fig. SM6).

Traces of climate change were detectable during the three decades of the experiment, though no significant trend was found regarding precipitation and evapotranspiration-related indicators. On the other hand, the frequency of weather extremes especially in the flowering period changed considerably in the past 30 years. The number of precipitation days shows a clear though not significant declining trend in this period. In the first two decades of the experiment, there was one year per decade with less than 10 rainy days in the flowering season. In the last decade, there were six such years. The number of hot days more than doubled during 30 years. As the technological level of cultivation has not changed during the study period, and the yield potential of the new varieties is certainly no worse than before, climate change is most likely the main cause of the observed changes. Mainly due to the increased heat stress coupled with considerable atmospheric drought around anthesis the expectable yield levels have decreased by more than 21%. Similar results have been reported in previous national (Fodor et al. 2014) and international (Webber et al. 2018) crop modelling studies.

The two models presented in this paper fit linear terms for time trends. In order to explore the effect of environmental factors, we additionally used annual and monthly meteorological data as covariates in the final single response surface model. A total of 58 models adding one of the 58 covariates were fitted. The added covariate was not significant in most of the cases. In case of significance, the year variance was reduced up to 40% or increased up to 4%. Furthermore, time trend was increased or decreased by up to no more than 10%. No changes on other regression coefficients including time-by-FAO classification interactions were found (results not shown). Note that covariate values vary between years only, but not between plots. Thus, it is to be expected that their inclusion in the model can only affect time trend but no effect of other factors varied in the experiment. Further note that these additional analyses do not provide any causal inference, as the environmental covariate data is purely observational.

According to Shim et al. (2017) the decrease in kernel number accounted for a much greater contribution to the yield reductions due to temperature elevation than did the decrease in individual kernel weight in maize cultivars. Partial pollination caused by heat stress seems to be the actual cause of yield reductions that cannot be mitigated with higher nitrogen fertilization doses. Increasing fertilization doses above a certain level won't result in higher yields and certainly will not realize higher revenues. The stagnating nitrogen fertilization optimums coupled with the decreasing yield levels mean gradually increasing production costs. The fact that the same optimum N fertilization level is sufficient to achieve lower and lower yields calls into question the view that intensification could promote sustainable development in this climatic region.

Medium-early hybrids are less affected by the environmental changes than the late hybrids because their flowering phase overlaps much less with the critical, stressful period. Three decades ago, late varieties yielded 15% more than medium-early varieties, but nowadays medium-early varieties yield nearly 10% more.

Depending on external (abiotic stress status) and internal (maturity group) factors the planting date optima may differ by a month across the years. Even on average, the optimal planting date has now shifted into the first decade of April in accordance with other studies (Marcinkowski and Piniewski 2018; Yasin et al. 2022). As the likelihood of unfavorable years is expected to increase in the future, earlier planting, even before 1st of April, may become an effective mitigation option. Since the likelihood of extreme weather events is also expected to increase with climate change there is still the question of whether the simple "early sowing" as a mitigation option will be feasible at all, despite the late frosts that may occur. The chance of late frosts (days with $T_{min} < 0$ °C) in the 03.21–04.10 period is currently around 10% at the study area. According to 10 available climate projections for the region (Kern et al. 2024), toward the end of the century, this likelihood is estimated to decrease down to 3.6 and 1.0%, whether RCP4.5 or RCP8.5 scenarios are considered, respectively.

3.5 Impact assessment of fertilization on soil quality

No significant difference (at α = 0.05) could be observed between the SOC content in 1989 and the SOC content of the different fertilization treatments in 2018, based on a Mann-Whitney *U*-test and a Permutation test (Good 2005). It seems that incorporating more byproducts into the soil, despite the removal of more grain, may help to prevent the loss of soil organic matter when more biomass is produced with improved nutrition. The SOC content was not significantly affected by nitrogen doses at any depth, suggesting that no long-term effect of fertilization on soil quality was observed. The effect of changes in soil quality over the study period on the results appears to be negligible.

3.6 Crop modelling results

Performance of the calibrated Biome-BGCMuSo model in simulating maize yield is demonstrated in Fig. 7. After calibrating the selected plant-specific parameters, the model was capable of estimating the observed values with a comparable efficiency reported in similar studies (Bao et al. 2017; Sándor et al. 2017; Soufizadeh et al. 2018; Diancoumba et al. 2024). Figure 7 also conveys an important message: The Biome-BGCMuSo model cannot accurately calculate county-level yields from year to year, but it can simulate average yields over longer periods with reasonable accuracy at NUTS-3 level. For the purpose of this study, this latter capability of the model is sufficient, as we only want to predict the trend of changes in average yields over longer periods.

Mainly due to the mid-summer heat waves and the droughty Augusts that are becoming more and more frequent, maize yields are projected to decline significantly towards the end of the century (Fig. 8). In particular, regions with above-average yields, immediately west of the Danube and in the south-west, are expected to suffer significant yield losses of more than 25%. These results are in good agreement with previous modelling studies showing that, without mitigation strategies (BAU management), climate change is expected to have negative impacts on maize in the Carpathian basin (Webber et al. 2018). However, earlier sowing, an easy and inexpensive change in management (Minoli et al. 2022), can reduce yield losses to below 15% in almost the whole study area. In the wetter areas of the region, western and north-eastern Hungary, this mitigation option can even fully offset the negative impacts of climate change (Fig. 8).

Despite decades of development of process-based crop and terrestrial ecosystem models, the accurate simulation of interannual variability remains an unresolved challenge (Ostberg et al. 2018; Leng and Hall 2020; Lin et al. 2023). Though underestimation of year-to-year yield variability represents a significant challenge to the utilization of these models for short-term decision-making, the statistical model, based on observations, and the process-based simulation model, demonstrate consistent long-term trends.

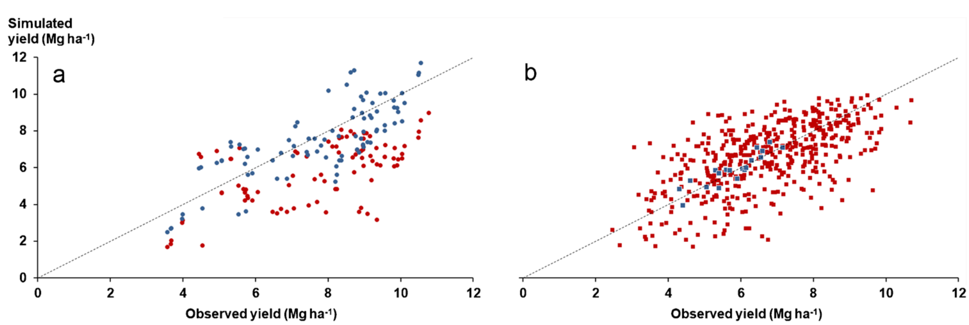

Fig. 7 **a** Observed and simulated yields before (red circles) and after (blue circles) calibration using site-specific weather and soil data from Martonvásár (1992–2021), Hungary; **b** Observed and simulated yields of model validation using NUTS-3 level observed data from Hungary consisting 19 NUTS-3 regions: annual values (red squares) and values aggregated for the 2001–2020 period (blue squares). Dotted line represents the "1:1 line". Model performance indicators before vs after calibration: CCC = 0.376 vs 0.788, MSE = −1.98 vs −0.25 Mg ha^{-1}, MAE = 2.20 vs 1.08 Mg ha^{-1}. Performance indicators of model validation for annual vs aggregated values: CCC = 0.595 vs 0.887, MSE = −0.13 vs 0.11 Mg ha^{-1}, MAE = 1.22 vs 0.33 Mg ha^{-1}.

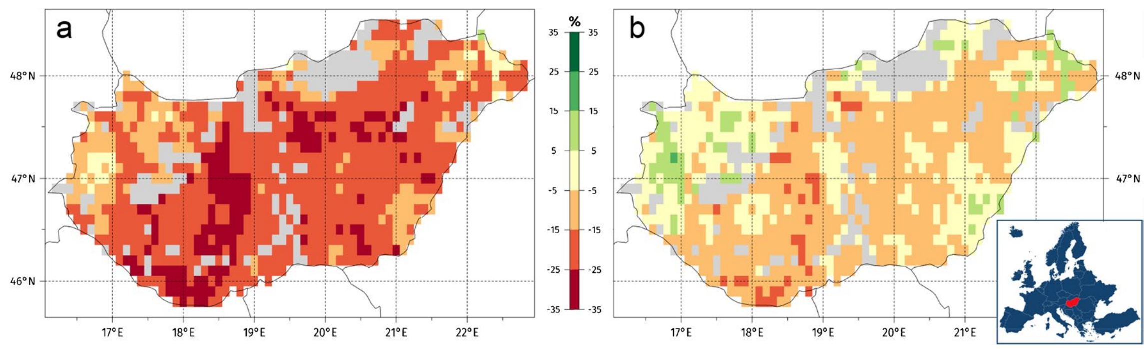

Fig. 8 Changes of average maize yields in Hungary: 2081–2100 period compared to the baseline (2001–2020) period. **a** According to unchanged sowing time (BAU) simulations; **b** according to 3 weeks earlier planting time (3WEP) simulations. The embedded map in the bottom-right corner shows the size and position of Hungary within Europe. Grid cells where the proportion of arable lands is less than 20% are masked in grey.

3.7 Cost-benefit analysis of the possible mitigation options

Sowing earlier does not affect most production cost elements: soil preparation, seed, crop protection, machinery, and labor costs do not change because the sowing time changes. The higher N fertilizer rates required for higher yields due to the earlier optimal planting date mean more fertilizer use and therefore higher costs only in relative terms. In absolute terms, the amount of N fertilizer needed to achieve maximum yields does not change over time (Fig. 6a), so this cost element does not change with earlier planting. Our observations show a negative correlation between earlier planting and grain moisture content at harvest, so if the harvest date does not change, earlier planting will reduce drying costs. If the harvest date is also moved forward, the reduction in drying costs may not be realized, but a positive effect on crop rotation is more likely: With the additional time before the next (fall) crop is sown, nutrient release from the soil can be enhanced. Cover crops can help retain more nitrogen in the root zone. Tillage timing can also be better optimized, reducing the risk of forced soil management.

In conclusion, bringing the sowing date earlier is not expected to have a negative impact on costs. Consequently, it will also be a positive option for profit because of the increasing associated yields.

The selection of earlier maturing cultivars is a viable option, as is the strategic adjustment of the sowing date. The cost of production for these hybrids is not higher than that of the later maturing hybrids. In fact, the cost is often lower due to the lower cost of seed for early varieties in the region. However, this advantage is expected to disappear in the future if the market (the seed companies) also realizes that with climate change, the competitive advantage of late hybrids is a thing of the past.

The Carpathian Basin is a significant producer of maize, accounting for approximately 25% of the EU's total maize production. The region's climate is expected to be affected by a number of impacts due to climate change that will adversely affect maize production. The mitigation strategies examined have clear economic benefits for the region and do not require difficult preparatory steps to implement. Other studies also show that the changes in agricultural management that we have studied could be beneficial in other regions as well (He et al. 2021; Kafaie Ghaeini et al. 2023). The necessity of detailed local studies concentrating on smaller regions is evident, as the efficacy of a given mitigation option is not uniform across all areas. For instance, research indicates that in other locations later-maturing maize hybrids may potentially offer higher yields under future climate conditions compared to earlier-maturing ones (Markos et al. 2023).

3.8 Limitations of the study

While the research offers valuable insights, it is important to note that it is not without its limitations. A key limitation of the study is the reliance on a single-site observation. A substantial amount of data was collected over a considerable (30-year long) period. The reliability of the trends identified can be statistically validated. The statistical model employed assumes a quadratic response with respect to the primary input variables, and the goodness of fit was satisfactory based on the lack of fit tests we conducted (Table SM1). Other nonlinear regression approaches could have been explored, including P-splines, but these would come at the cost of somewhat increased complexity. The quadratic model is a satisfactory compromise between explanatory power and complexity.

The Pannonian region was purposefully selected due to its climatic homogeneity, which renders it of significant importance with respect to European maize production. Despite occupying a mere 3% of the EU's total territory, this region is responsible for around 25% of the EU's maize production. In the development of the statistical model, it would have been advantageous to utilize the findings from other long-term experiments; however, no stations in this region were identified in the BONARES - European agricultural long-term experiments database (Donmez et al. 2022) that had examined the effects of Variety × Fertilization × Planting date analogous to the Martonvásár complex experiment. In light of the substantial correlation that was observed, it can be concluded that the yield results of the long-term experiment serve as a reliable indicator of yields in the region. Similar to other studies (e.g., Pasquel et al. 2022) site-specific results were spatially extended using a process-based crop model. The crop model confirmed the results of the statistical model (cf. Fig. 6c and Fig. 8).

Another key limitation of the study is that the crop model simulations were carried out only for Hungary. The country is situated in the central portion of the study region, encompassing approximately 45% of the Carpathian Basin. A substantial part of the basin is situated within the borders of Romania, with these two nations collectively encompassing nearly 90% of the total area. According to the observations made during the period under study, there is a strong, statistically significant positive correlation (r = 0.72) between the yields of the Hungarian and Romanian areas. This allows us to state with great confidence that the modelled trends obtained for the Hungarian areas are valid for the whole Pannonian basin. The rationale behind conducting the modeling exclusively for Hungary pertains to the availability of reliable and high-resolution climate and soil databases, which are only accessible for this specific region. It is important to note that the Biome-BGCMuSo model used in this study has demonstrated remarkable efficacy in numerous international intercomparison studies (Kimball et al. 2023, 2024).

4 Conclusion

This study aimed to analyze a 30-year period of a multi-factorial long-term experiment, with the goal of detecting traces of climate change in yield trends and identifying favorable combinations of agro-management factors that could serve as effective adaptation options for the future. We may conclude that late hybrids seem to have no perspective in the Pannonian climatic zone. Early sowing, shifting the planting date even into the last decade of March, will come with only a marginal chance of losing crop due to frost damages when approaching the end of the century.

Sub-optimal environmental conditions may greatly change the effect of certain agro-management factors. In bad years the differences in hybrid selection or in the level of nitrogen fertilization may result in a much greater impact on the yield than in good years (Fig. SM4-5). When planning nitrogen fertilization levels, the planned planting date also should be taken into account as it clearly influences the fertilizations level optimum. Additionally, fertilization recommendations could be adjusted after a bad year to account for the considerable amount of nutrients that was not taken up, taking into account the possible immobilization. The harmonization of planting date, fertilization level and variety selection for obtaining the achievable yield is crucial especially in bad years. Generally speaking, the determination of the optimum of any of the investigated factors is only possible if the other two are taken into account. This principle should be taken into account in the next generation of plant production related advisory systems. This is the first comprehensive study that combines long-term historic weather data, high-resolution soil data, climate projection data as well as statistical and crop simulation modelling tools in order to provide reliable mitigation strategies for farmers and policy makers. Research indicates that while farmers may be aware of climate change, there is often a discrepancy between perception and the implementation of adaptation strategies. This discrepancy can be attributed to a strong attachment to traditional farming practices and skepticism towards new methods (Amadou et al. 2022; Yazdanpanah et al. 2023). Therefore, effective knowledge transfer is essential to encourage farmers to adopt new practices. The implementation of these anticipated beneficial measures (earlier planting, planting of early hybrids) is expected to enhance the region's competitiveness and export capacity, ensuring their sustainability in the future.

It is hypothesized that a longer time series will not yield significantly different results; a 30-year period is sufficient to establish trends. However, the reliability of extending the conclusions spatially can be further increased by including more detailed soil and crop management data for areas of the Carpathian Basin outside Hungary. The study can be further elaborated by analyzing the spatial heterogeneity of the results and showing how and why sub-regions differ from each other.

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Authors' contributions Klára Pokovai: methodology, writing, editing
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All the authors read and approved the final manuscript.

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Data availability The datasets generated during and/or analyzed during the current study are not publicly available but are available from the authors on reasonable request.

Code availability Simulations were undertaken with the BiomeBGC-MuSo (v6.1) model. The code is available on request but permission is required to change it. ASReml and SAS codes are also available on request.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

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