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Human-induced climate change has decreased wheat production in northern Kazakhstan

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Human-induced climate change has decreased wheat production in northern Kazakhstan

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Abstract

Northern Kazakhstan is a major wheat exporter, contributing to food security in Central Asia and beyond. However, wheat yields fluctuate and low-producing years occur frequently. It is currently unclear to what extent human-induced climate change contributes to this. The most severe low-producing year in this century was in 2010, which had severe consequences for the food security of wheat-importing countries. Here, we present a climate impact attribution study that quantifies the impact of human-induced climate change on the average wheat production and associated economic revenues in northern Kazakhstan in the 21st century and on the likelihood of a low-production year like 2010. The study uses bias-adjusted counterfactual and factual climate model data from two large ensembles of latest-generation climate models as input to a statistical subnational yield model. We consider the climate data and the yield model as fit for purpose as first, the factual climate simulations represent the observations, second, the out-of-sample validation of the yield model performs reasonably well with a mean R^2 of 0.54, and third, the results are robust under the performed sensitivity tests. Human-induced climate change has had a critical impact on wheat production, specifically through increases in daily-minimum temperatures and extreme heat. This has resulted in a decrease in yields during 2000–2019 by approximately 6.2%–8.2% (uncertainty range of two climate models) and an increased likelihood of the 2010 low-production event by 1.5–4.7 times (10th to 90th percentile uncertainty range covering both climate models). During 2000–2019, human-induced climate change caused economic losses estimated at between 96 and 180 million USD per year (10th to 90th percentile uncertainty range covering both climate models). These results highlight the necessity for ambitious global mitigation efforts and measures to adapt wheat production to increasing temperatures, ensuring regional and global food security.

1. Introduction

Wheat production is essential for global food security, providing over 20% of the world's total calorie intake (Lephuthing *et al* 2021). High-producing and exporting regions are especially important, northern Kazakhstan being one of them. In 2020, Kazakhstan ranked 14th in terms of wheat production, with a national output exceeding 14 million tonnes (FAO 2024). However, wheat production and exports are highly

Figure 1. The observed 2010 climate event in comparison to the long-term average. (a), (b) The spatial extent of the a) total precipitation [mm] and (b) mean maximum temperature [°C] anomaly of 2010 in northern Kazakhstan during the growing season between May and September. (c), (d) Climate diagrams covering the average over the three oblasts for (c) 1993–2019 and (d) 2010.
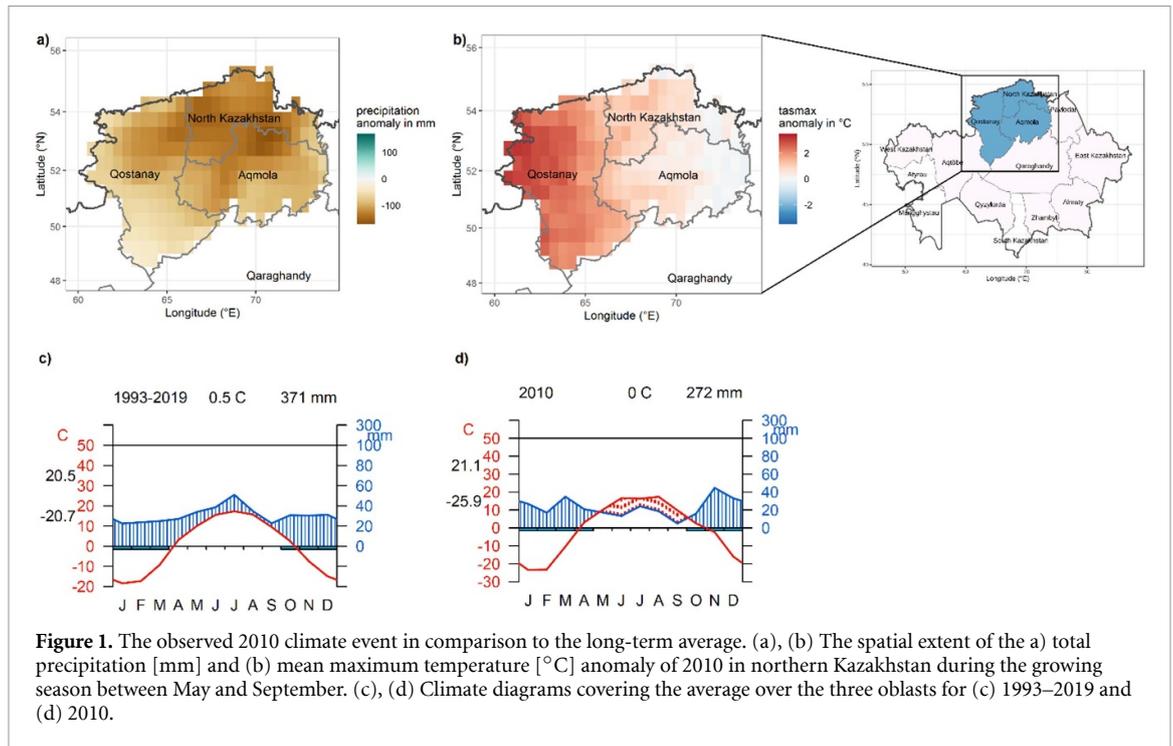
variable (FAO 2024), affecting food security in wheat-importing regions. The impact of climate change on wheat yields and its variability in Kazakhstan are to date uncertain as climate impact studies in this region are sparse (Schierhorn *et al* 2020). This study addresses this research gap. It presents a climate impact attribution analysis for wheat production in Kazakhstan quantifying the impact of human-induced climate change on wheat production.

Wheat is the primary agricultural commodity in Kazakhstan and its production is concentrated in the northern oblasts[6] of Aqmola, North Kazakhstan, and Qostanay (in the following referred to, together, as northern Kazakhstan) (Bureau of National Statistics Kazakhstan 2022, FAO 2024). Rain-fed spring soft wheat dominates wheat cultivation (Lioubimtseva and Henebry 2012, Karatayev *et al* 2022). Yields are typically below 1.5 tonnes per hectare (Bureau of National Statistics Kazakhstan 2022), which is low compared to other world regions. Yields fluctuate with variable weather conditions (Fehér and Fieldsend 2019, Karatayev *et al* 2022), and droughts pose the highest risk of low crop yields (Shmelev *et al* 2021). Driven additionally by a varying production area, the total wheat production in northern Kazakhstan ranged from below 4 million tonnes in some years in the 1990s to almost 20 million tonnes in the high-producing year of 2011 (Bureau of National Statistics Kazakhstan 2022). This has a major impact on the amount of wheat exported (FAO 2024).

The lowest wheat yields in northern Kazakhstan in this century were recorded in 2010 with an average of 0.7 tonnes per hectare (Bureau of National Statistics Kazakhstan 2022). This was due to the combination of a severe drought and high temperatures (shown in figures 1(a)–(d)) (Lioubimtseva and Henebry 2012, Karatayev *et al* 2022). The heat wave in 2010 stretched over a large area of Kazakhstan, Ukraine, and Russia (KUR). The heatwave was centred in western Russia, which experienced the hottest summer in the last 500 years (Liu *et al* 2020, Karatayev *et al* 2022). The drought that followed extended even further east into Kazakhstan (Cherenkova *et al* 2015, figure 1(a)). Rahmstorf and Coumou (2011) attributed an increase in the likelihood of the heat wave in Russia in July 2010 to human-induced climate change. Followed by unfavourable weather conditions in 2010, Russia's wheat production decreased by 33% and Ukraine's decreased by 20% (Svanidze *et al* 2022, FAO 2024). Due to the low production, Kazakhstan exported little in 2011 (Oshakbayev 2012) and Russia and Ukraine imposed export restrictions on wheat (Fellmann *et al* 2014). These actions could not isolate domestic bread prices from the volatility of world wheat prices (Götz *et al* 2015). The coinciding wheat losses and low export rates in KUR resulted in a rapid increase in wheat prices worldwide and in negative global-scale impacts on food security (Broka *et al* 2016, Loboda *et al* 2016, Hunt *et al* 2021). In the 9 months, from June 2010 to February 2011, the food price index increased by about 25%, the world wheat prices doubled, and bread prices regionally increased by up to 300% (Hunt *et al* 2021). This led to the risk of economic inaccessibility of the most essential item of the food basket for several

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[6] Administrative unit

countries in western Asia and North Africa and had a detrimental effect on the poorest segments of the population, increasing poverty rates (Klasen 2018, Hunt *et al* 2021).

Modelling results suggest that the observed rise in temperature has already negatively affected wheat yields in most growing regions of the world and that wheat production is becoming more variable (Asseng *et al* 2014). The IPCC states, with low confidence, that human-induced climate change has today mixed positive and negative impacts on wheat production in Central Asia (Bezner Kerr *et al* 2022). Studies at a global level estimate a decrease or no significant change in Kazakh wheat yields due to anthropogenic climate forcing (Lobell *et al* 2011, Lobell and Gourdji 2012, Iizumi *et al* 2018). A regional study by Schierhorn *et al* (2020) found that past climate trends had small impacts on wheat yields in Kazakhstan, although these impacts varied spatially.

The impact of human-induced climate change on agricultural production can be quantified through climate impact attribution analyses. Observed changes in a climate-related system can be attributed to human-induced climate change by comparing climate simulations with observed forcing (factual simulations) to climate simulations in the absence of anthropogenic forcing (counterfactual simulations) (Seneviratne *et al* 2021, Rawshan Ara Begum *et al* 2022; 'climate attribution'). Observed changes in natural, human or managed systems (here: wheat yields and export revenues) can be attributed to such changes in the climate-related system (Rawshan Ara Begum *et al* 2022; 'impact attribution'). In this study, we do both steps by explicitly modelling crop yields based on agroclimatic indices derived from climate model simulations that by design either include (factual) or exclude (counterfactual) the response of the climate system to anthropogenic forcings ('climate impact attribution').

In this study we attribute the impacts of climate change on agricultural production by simulating yields with a statistical yield model fed with sets of climate simulations that include (factual) or exclude (counterfactual) known human influences on the climate since pre-industrial times (reference year 1850). Thereby, we quantify whether and if so how much influence human-induced climate change has had on wheat production in the high-producing regions of Kazakhstan and on the Kazakh economy during 2000–2019. Additionally, we focus on the extreme year 2010 and estimate the change in the likelihood of yields as low or lower than in this year specifically. Only very few studies to date make use of counterfactual and factual model realisations to attribute the impact of human-induced climate change on crop yields (Iizumi *et al* 2018, Sultan *et al* 2019, Verschuur *et al* 2021), and such studies on Central Asia or Kazakhstan are, to our best knowledge, not available.
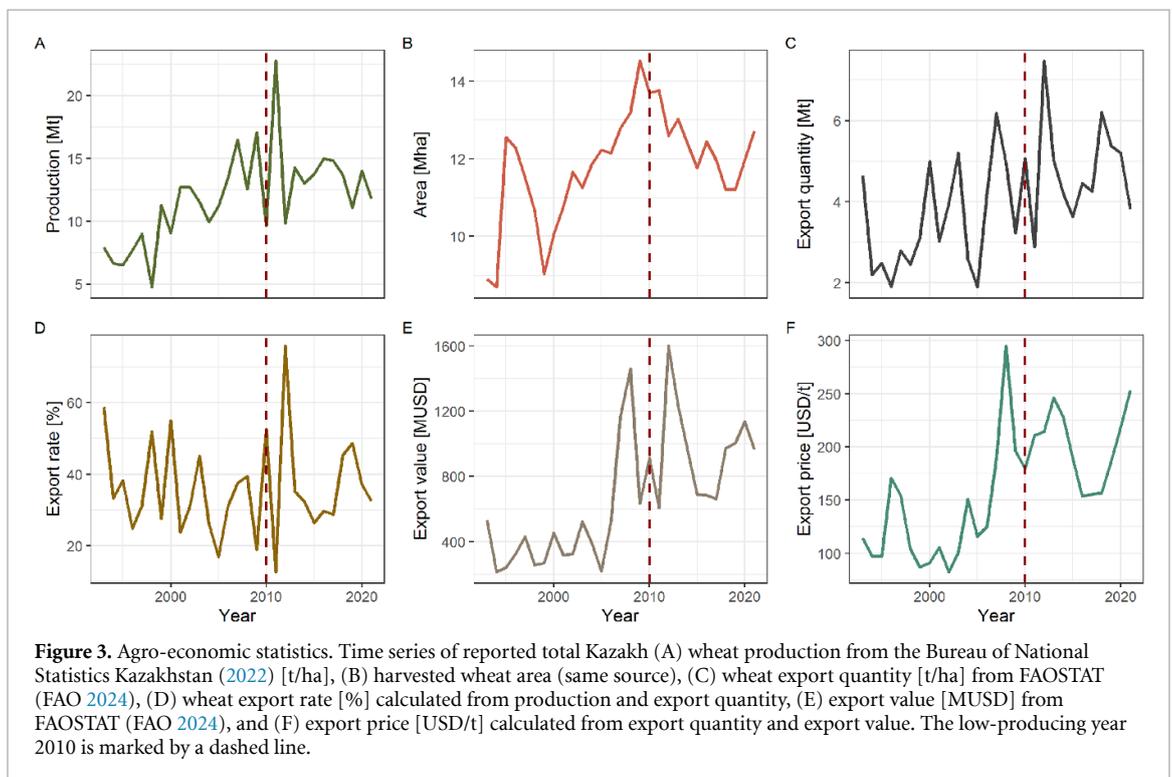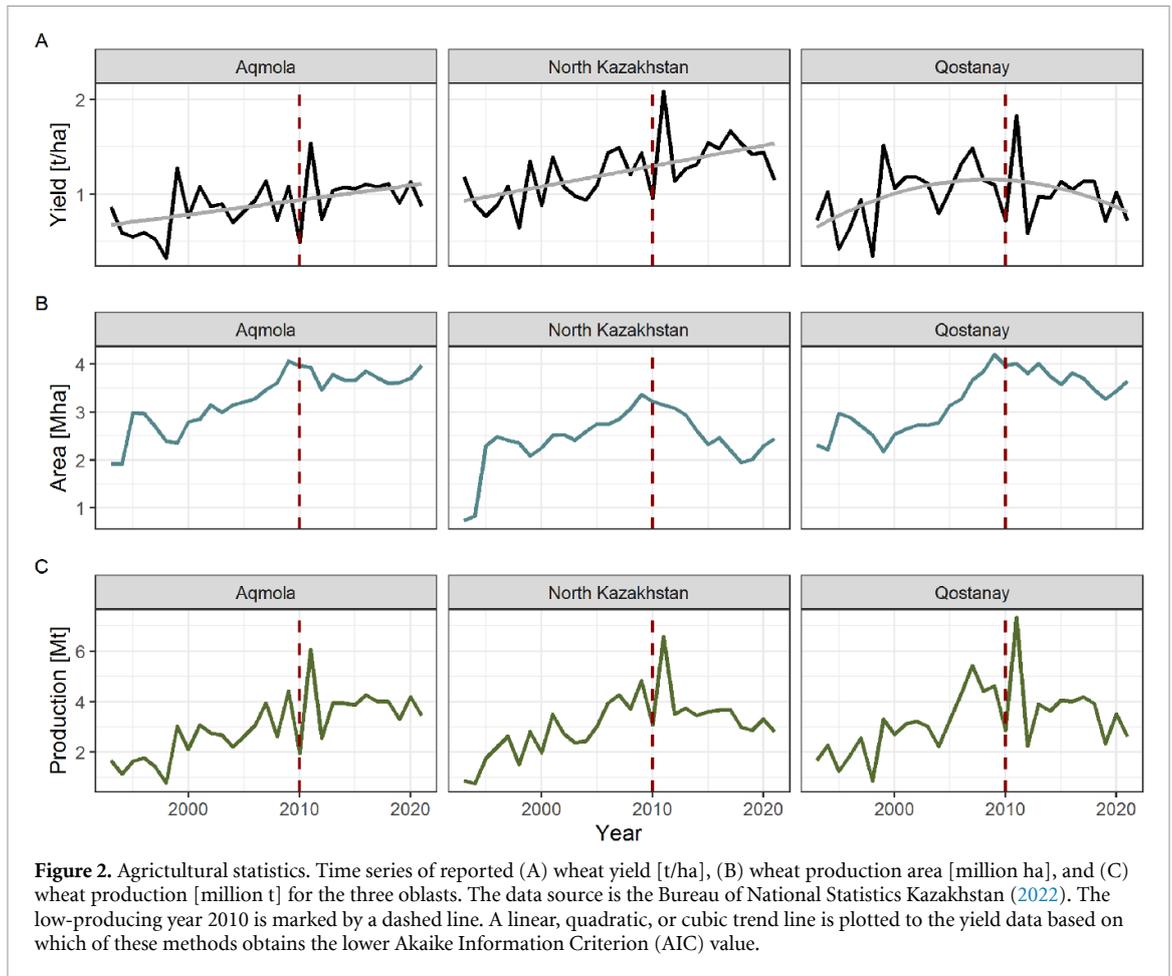
2. Data and methods

2.1. Input data and data evaluation

We obtained data on yield, production, and production area at the oblast level for Aqmola, North Kazakhstan, and Qostanay from the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (Bureau of National Statistics Kazakhstan 2022; figure 2). Data on export quantity and export value was obtained from FAOSTAT (FAO 2024; figure 3).

Observational precipitation and temperature data were obtained from W5 $\times$ 10^5 v2.0 (Cucchi *et al* 2020, Lange *et al* 2021), a reanalysis data set with a spatial resolution of $0.5° \times 0.5°$. W5 $\times$ 10^5 is over land based on WFDE5 (WATCH Forcing Data methodology applied to ERA5 data and monthly values are bias-adjusted with CRU) whereby precipitation is adjusted to Global Precipitation Climatology Centre.

We took factual and counterfactual climate simulation data from two large ensembles that are part of the Coupled Model Intercomparison Project Phase 6 (CMIP6; Eyring *et al* 2016). These are namely the sixth version of the Model for Interdisciplinary Research on Climate (MIROC6) (Tatebe *et al* 2019) and the Canadian Earth System Model version 5 (CanESM5) (Swart *et al* 2019), each consisting of 50 realisations. For CanESM5, the simulations with physics index values p1 and p2 were pooled as the difference between them is negligible for this purpose (Swart *et al* 2019). The factual data consists of historical data with all (anthropogenic and natural) forcings until 2014 extended with SSP2-RCP4.5 until 2019, following the Detection and Attribution Model Intercomparison Project (DAMIP) protocol (Gillett *et al* 2016). The counterfactual data consists of historical runs that exclude anthropogenic forcings ('hist-nat' in Gillett *et al* 2016). The different realisations vary between each other due to different internal climate variability manifestations. The comparative use of such datasets from two climate models allows us to account for some climate model uncertainties. The climate model data was corrected for their biases compared to the W5 $\times$ 10^5 dataset using a trend-preserving parametric quantile mapping that is also used to provide the ISIMIP3b climate forcing input data (Lange 2019, Lange *et al* 2021, Frieler *et al* 2024). Bias-adjusting the raw model data was necessary because most of the agroclimatic input variables to the yield model are based on absolute values. The need for a multivariate model also implied difficulties with an indirect bias-adjustment method that would compare modelled/observed return periods regardless of biases in the corresponding absolute

Figure 2. Agricultural statistics. Time series of reported (A) wheat yield [t/ha], (B) wheat production area [million ha], and (C) wheat production [million t] for the three oblasts. The data source is the Bureau of National Statistics Kazakhstan (2022). The low-producing year 2010 is marked by a dashed line. A linear, quadratic, or cubic trend line is plotted to the yield data based on which of these methods obtains the lower Akaike Information Criterion (AIC) value.

Figure 3. Agro-economic statistics. Time series of reported total Kazakh (A) wheat production from the Bureau of National Statistics Kazakhstan (2022) [t/ha], (B) harvested wheat area (same source), (C) wheat export quantity [t/ha] from FAOSTAT (FAO 2024), (D) wheat export rate [%] calculated from production and export quantity, (E) export value [MUSD] from FAOSTAT (FAO 2024), and (F) export price [USD/t] calculated from export quantity and export value. The low-producing year 2010 is marked by a dashed line.

values as common in climate event attribution studies. Bias-adjustment on the grid-box level was desirable for the use of peer-reviewed data processing pipelines (Romanovska *et al* 2023) and for comparability with a possible follow-up study using gridded crop models. Using the ISIMIP3 method had the further advantage of
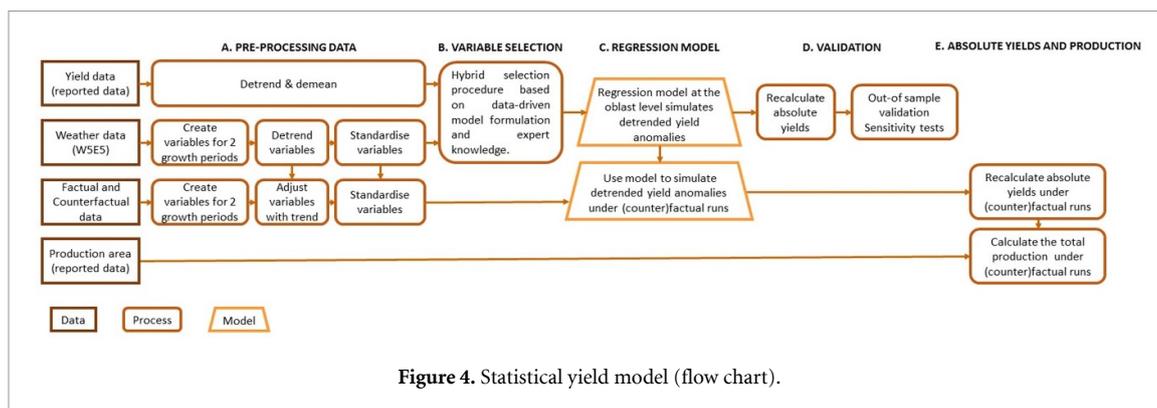
Figure 4. Statistical yield model (flow chart).

providing maximum similarity to impact modelling as commonly applied to future projections (for example Jägermeyr *et al* 2021). Here, the bias-adjustment was performed on the native spatial resolution of each model (MIROC6: $1.4° \times 1.4°$; CanESM5: $2.8° \times 2.8°$). Then, we conservatively remapped the CanESM5 and $W5 \times 10^5$ data to the native spatial resolution of MIROC6 ($1.4° \times 1.4°$) to ensure consistency in grid boxes.

The climate model data was evaluated by visually comparing the distributions of :

(1) agroclimatic variables based on factual climate data versus $W5 \times 10^5$ data from 1979 to 2019
(2) yields simulated with factual climate data versus observed yields from 2000 to 2019.

2.2. Statistical yield model

To simulate yields at the oblast level, we developed a statistical regression model following the approach by Gornott and Wechsung (2016), Laudien *et al* (2022), Schauberger *et al* (2017), and Romanovska *et al* (2023) using yield and observed agroclimatic variables from 1993 to 2019. Next, we applied the model to the factual and counterfactual climate data. The steps are visualised in figure 4 and in detail explained below.

2.2.1. Pre-processing of yield and climate data

To remove any long-term trends caused by changes in management, we detrended the yield time series using the method (mean, linear, quadratic, or cubic) that produced the lowest Akaike Information Criterion (AIC) value. We took the anomalies of the detrended yields as model input.

Based on daily maximum and minimum temperature and precipitation, we created 19 physiologically meaningful agroclimatic variables that describe either potential stress or growth factors (listed in SI section 1 table S1), following Romanovska *et al*'s (2023) crop model. The agroclimatic variables were defined for the growing season between May and September, if not indicated differently. They were calculated at the grid level and then averaged over the oblast area to obtain one value per oblast.

The agroclimatic variables were calculated separately for the whole growing season, as well as the vegetative and reproductive phases seperately, distinguished based on the sum of growing degree days (GDDs, defined in table S1). The vegetative phase was defined as the period of days in the growing season until 50% of the full-season GDD sum was reached and the remaining days were allocated to the reproductive phase, following Laudien *et al* (2020) and Schauberger *et al* (2017). All agroclimatic variables were calculated for the observed climate data ($W5 \times 10^5$), as well as for the counterfactual and factual data sets.

Next, we detrended the variables for the observed climate ($W5 \times 10^5$) using the same method (mean, linear, quadratic, and cubic) that was selected for the yield detrending. To improve the interpretability of the model coefficients we standardised the variables to z-scores by subtracting the mean and dividing this by each variable's standard deviation. We also detrended and standardised the agroclimatic variables from the counterfactual and factual climate data sets based on the trend, mean, and each variable's standard deviation in the observations.

2.2.2. Variable selection

We selected the six most suitable agroclimatic variables. The selection procedure was partly data-driven, partly based on expert knowledge, combining the advantages of both approaches. Following Romanovska *et al* (2023), we selected variables for the regression model at the oblast level using LASSO. Initially, we removed collinear variables (Pearson correlation coefficient >0.7) by retaining only the one variable with the highest correlation to yield anomalies. We forced LASSO to iteratively select between two to eight variables (i.e. producing seven separate crop model runs) for each oblast, observed the simulating skills of the respective regression model at the oblast level and counted how often each variable was selected. To ensure

comparability of the results across the three oblasts, we developed a skilful and interpretable model based on the same variables for all oblasts. We selected six variables for the final model based on two criteria: First, the variables were often selected by LASSO, and, second, they cover the most important weather stress and growth factors for wheat in northern Kazakhstan.

2.2.3. Regression model

Based on these six agroclimatic variables, we developed a linear regression model for each oblast following equation (1)

$$y_{ti} = \beta_{0i} + \sum_{j=1}^{J} \beta_{ji}x_{jti} + \varepsilon_{ti} \tag{1}$$

y—detrended and demeaned response variable (i.e. yield);
β—beta coefficient;
β_0—intercept;
x—detrended and standardized input variables (i.e. agroclimatic variables);
ε—error term;
t—T years ($t = 1,\ldots, T$);
i—N spatial units (i.e. oblast) ($i = 1,\ldots, N$);
j—J variables ($j = 1,\ldots, J$); $J = 6$.

2.2.4. Model validation

We performed the Shapiro–Wilk test checking for a normal distribution of model residuals. A *p*-value above 0.05 does not reject the null hypothesis that the model residuals are normally distributed. Additionally, we conducted the Breusch–Pagan test against the heteroscedasticity of model residuals. A p-value above 0.05 does not reject the null hypothesis that the model residuals are distributed with equal variance. To explain the extent to which our input variables (agroclimatic variables) can explain our output variable (yield) we used the standard model evaluation index R^2 (coefficient of determination). The skill of the yield model was further assessed through an out-of-sample validation where we subsequently removed one year from the data set, and refitted the coefficients to simulate yields for the removed year. Additionally, we conducted a sensitivity test by re-running the model six times based on only five out of the six agroclimatic variables, leaving out each variable subsequently.

2.2.5. Recalculating actual yields and total production

We transformed the detrended, simulated yield anomalies under the different scenarios and climate models back to their absolute values. These, we used to calculate the simulated total production in northern Kazakhstan by multiplication with the harvested production area and taking the sum over the three oblasts.

2.3. Climate impact attribution

We applied the climate impact attribution to two different questions: firstly, how much did the wheat production and subsequent export revenues in the 21st century change under human-induced climate change? And secondly, how did the likelihood of a low-production year, such as 2010, change?

As a first step we analysed the impact of human-induced climate change on the climate conditions for wheat growth by comparing the six selected agroclimatic variables from 2000 to 2019 in the factual and counterfactual simulations. An unpaired t-test was used to determine if the differences are significant at a level <0.05. To ensure sufficient data points we pooled all simulations from the years 2000–2019 from 50 model realisations per climate model, resulting in 1000 years per climate model (50 ensemble members × 20 years). Using a period instead of a single year is common in event attribution studies that use CMIP data (Seneviratne *et al* 2021) because such simulations are not conditioned to that year's sea surface pattern or state of atmospheric circulation anyway, so the only error this introduces is the variation of climate forcings (anthropogenic, volcanic, and solar) within that period.

To attribute the impact of human-induced climate change on yields, we compared the yields simulated under factual and counterfactual climate realisations from 2000 to 2019. Based on crop yield simulations and the observed wheat area we obtained the total wheat production for either case. We tested if the differences in production are significant with an unpaired t-test. Finally, we calculated the impact ratio ΔP of the total wheat production between 2000 and 2019 averaging over all model runs and years (equation (2)). The impact ratio quantifies the change in production resulting from human-induced climate change as a percentage. A negative value indicates a loss, while a positive value indicates a gain due to human-induced climate change

$$\Delta P = \frac{\sum_{i=1}^{N}\sum_{r=1}^{R}\sum_{t=t_0}^{T}\left(Y_{\text{factual},r,t,i} \times A_{t,i} - Y_{\text{counterfactual},r,t,i} \times A_{t,i}\right)}{R \times \sum_{i=1}^{N}\sum_{t=t_0}^{T}\left(Y_{\text{observed},r,t,i} \times A_{t,i}\right)} \quad (2)$$

ΔP—impact ratio;
Y_{observed}—observed yield;
Y_{factual}—simulated yield under the factual scenario;
$Y_{\text{counterfactual}}$—simulated yield under the counterfactual scenario;
A—harvested wheat area;
i—N spatial units (i.e. oblast; $N = 3$) ($i = 1,\ldots, N$);
r—R Climate model simulation runs (i.e. $R = 50$) ($r = 1,\ldots, R$);
t—(T-t_0) temporal units (i.e. years; $t_0 = 2000$; $T = 2019$) ($t = t_0,\ldots, T$).

We estimated the influence of human-induced climate change on the probability of a low-production event like 2010 with the risk ratio (RR). The RR was first introduced by Allen (2003) and is commonly used in event attribution studies to quantify weather and how much the probability of a class of events has changed due to anthropogenic influence on the climate (Perkins-Kirkpatrick *et al* 2022). An RR range below (above) one indicates that the event is made less (more) likely by human-induced climate change. The RR is here calculated as the probability of yields below a certain threshold (e.g. wheat production of 2010) under factual climate (P_{factual})divided by the probability of yields falling below the threshold under counterfactual climate ($P_{\text{counterfactual}}$). Confidence intervals of the RR were determined by bootstrapping 100 000 times over all ensemble members (Efron and Tibshirani 1986). Specifically, the bootstrapping method randomly selected 1000 data points with replacements from the 1000 simulations available per climate model.

Years of weak harvest in Kazakhstan lead to low export rates peaking in the next year (compare figure 3). Thus, we quantify the economic impacts between 2000 and 2019 by multiplying the differences in wheat production between factual and counterfactual conditions with the observed export prices of the subsequent year.

3. Results

3.1. Climate model data evaluation
The distributions of all six agroclimatic variables, except for tmprange_sd_1, show reasonable agreement between W5 $\times$ 10^5 and the factual simulations as the median of the observed value falls within the 25th–75th percentile of the simulations (figure 5). The same is the case for observed and simulated yields under MIROC6. However, the simulated yields under CanESM5 underestimate the observed yields (figure 6).

3.2. Yield model evaluation
The six selected agroclimatic variables of the yield regression model are the standard deviation of the diurnal temperature range in the first growing phase (tmprange_sd_1), the mean daily-minimum temperature in the second growing phase (tasmin_2), the 99th percentile of daily-maximum temperature in the complete growing season (tmax99), the total precipitation between January and September (pr_JS), the total precipitation in the first growing phase (pr_1), and the number of 15 d dry spells in the first growing phase (dry15_1). The model performance at the oblast level shows R^2 values ranging between 0.71–0.78 for the complete model run and R^2 values of 0.48–0.63 for the out-of-sample validations (figure 7). The simulations for the low-yielding year of 2010 are in agreement with the observations. The model coefficients display the same sign across all three respective models at the oblast level (figure 8). Residuals were normally distributed for all oblasts except for North Kazakhstan (Shapiro–Wilk test, $p = 0.022$). Heteroscedasticity did not appear for any of the oblasts (Breusch–Pagan test).

When rerunning the linear regression model with the subsequent removal of each variable in turn as a sensitivity test, the models' performance with five agroclimatic variables remained stable, with only slight increases or decreases in the R^2 values (for details, see SI section 2 and table S2).

3.3. Attributing weather conditions to anthropogenic climate forcing
The variables related to heat (tmax99) and minimum temperatures (tasmin_2) exhibit significant increases under simulations with anthropogenic forcing (figure 9). The standard deviation of the temperature range (tmprange_sd_1) shows slight increases under human-induced climate change, which are significant for Aqmola under both climate models and for North Kazakhstan under CanESM5. Precipitation between January and September is significantly higher under factual conditions. The other precipitation variables (pr_1 and dry15_1) do not show significant differences.
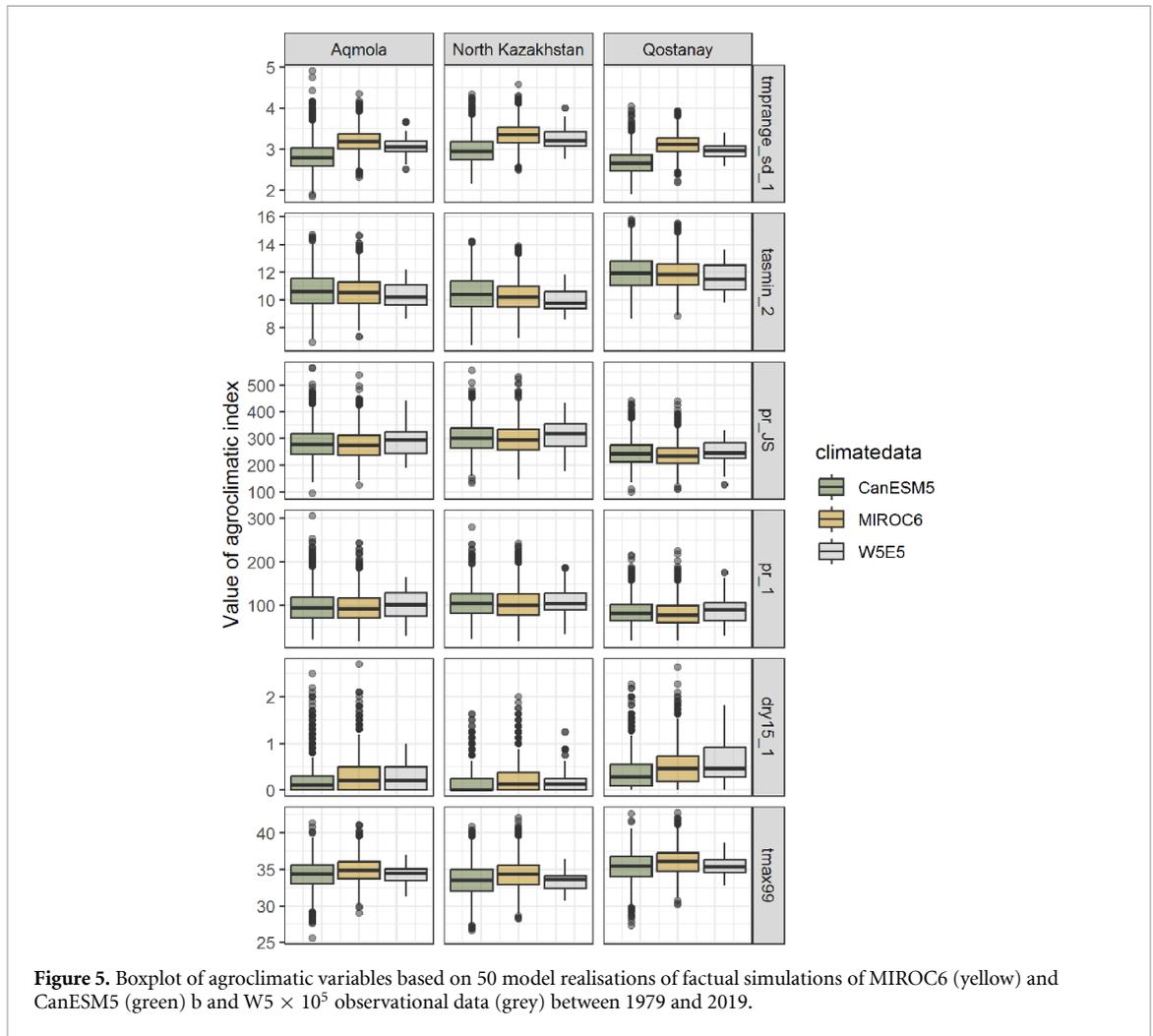
Figure 5. Boxplot of agroclimatic variables based on 50 model realisations of factual simulations of MIROC6 (yellow) and CanESM5 (green) b and W5 × 10⁵ observational data (grey) between 1979 and 2019.
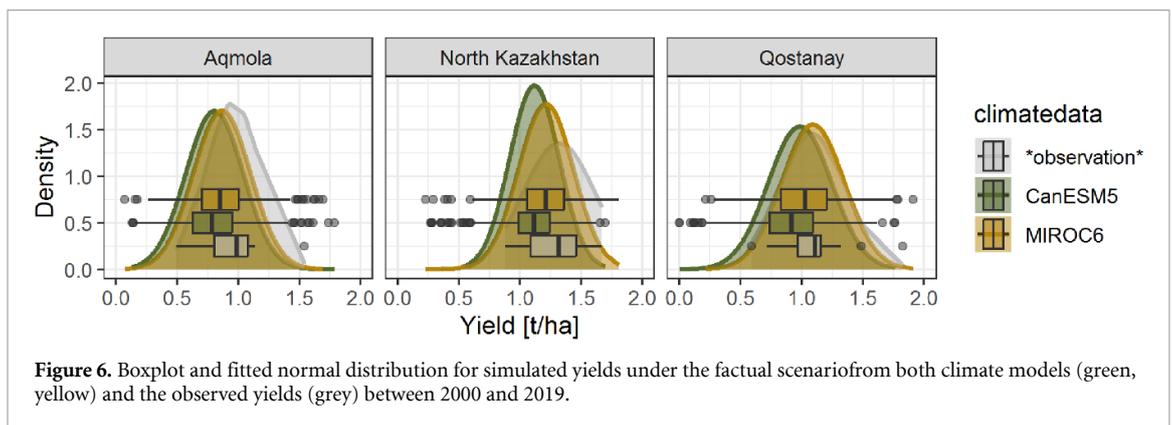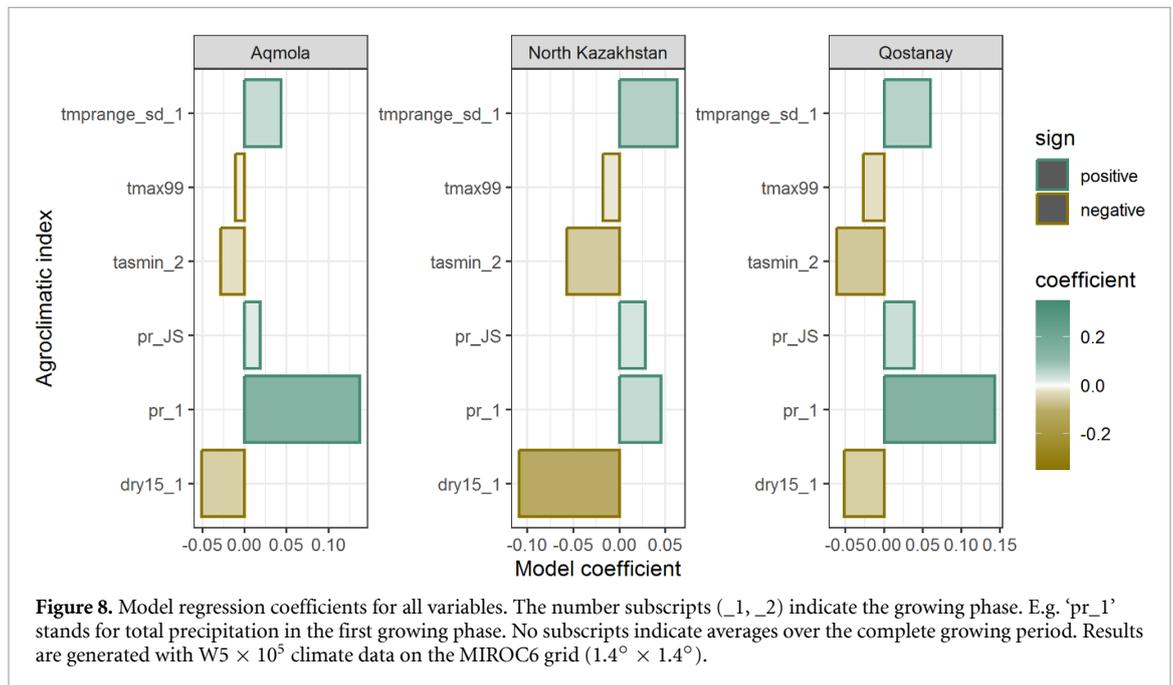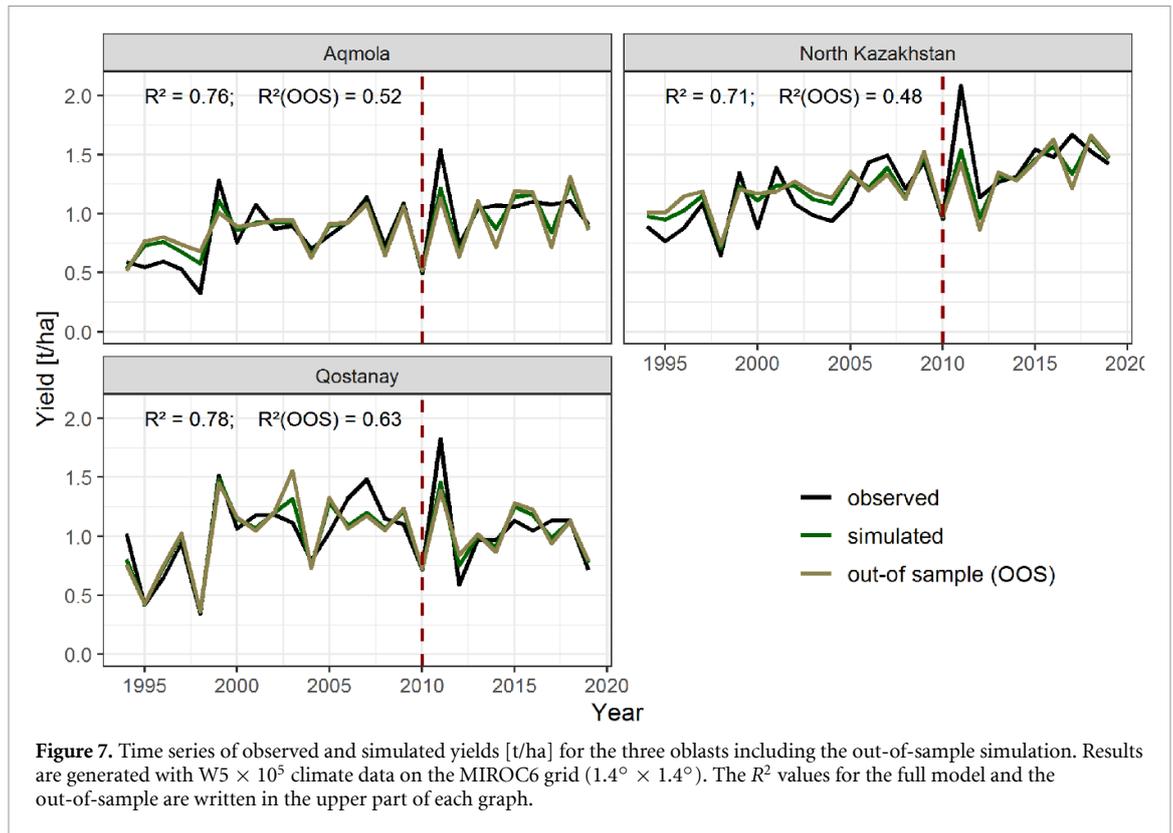

Figure 6. Boxplot and fitted normal distribution for simulated yields under the factual scenariofrom both climate models (green, yellow) and the observed yields (grey) between 2000 and 2019.

The weather conditions in 2010 were exceptional due to low precipitation (pr_JS and pr_1), many dry spells (dry15_1) and above-average values for the hottest days (tmax99). These conditions are visible in comparison to the factual simulations (figure 9 red dots).

3.4. Attributing yields, total production and economic revenues to anthropogenic climate forcing

According to both climate models, the yield simulations under factual and counterfactual conditions indicate that human-induced climate change led to a decrease in yields in all three oblasts between 2000 and 2019 (figure 10(a)). The differences are more pronounced in North Kazakhstan and Qostanay. The total production is significantly lower under factual conditions than under counterfactual conditions (figure 10(b), unpaired p-value $<10^{-12}$ for both climate models). The impact ratio ΔP derived here

Figure 7. Time series of observed and simulated yields [t/ha] for the three oblasts including the out-of-sample simulation. Results are generated with W5 $\times$ 10^5 climate data on the MIROC6 grid (1.4° $\times$ 1.4°). The R^2 values for the full model and the out-of-sample are written in the upper part of each graph.

Figure 8. Model regression coefficients for all variables. The number subscripts (_1, _2) indicate the growing phase. E.g. 'pr_1' stands for total precipitation in the first growing phase. No subscripts indicate averages over the complete growing period. Results are generated with W5 $\times$ 10^5 climate data on the MIROC6 grid (1.4° $\times$ 1.4°).

indicates that the total production between 2000 and 2019 decreased by 6.2% based on MIROC6 simulations and by 8.2% based on CanESM5 simulations due to human-induced climate change.

Observed and simulated yields successfully tested for a normal distribution (for details, see SI section 3 and figure S1). Utilizing the normal distribution of observed yields we determined the return period of the 2010 low-yielding event at the oblast level. Applying this return period to the normal distribution of simulated yields under the 1000 available simulations of the factual scenario, we obtained thresholds for the yields at the oblast level for the respective climate model. The same was done for the total production of wheat. We applied these thresholds to calculate the RR. The RR indicates that a low production year like 2010 is, due to anthropogenic climate forcing, 2.1 (best estimate; 10th to 90th confidence interval from 1.5 to 3.0) times more likely under MIROC6 simulations and 3.0 (2.1–4.7) times more likely under CanESM5

Figure 9. Boxplot of agroclimatic variables under the counterfactual and factual scenarios. The values are normalized based on the mean and standard deviation of observed (W5 × 10^5) agroclimatic variables. The red dot indicates the observed value in 2010 based on W5 × 10^5. The written numbers indicate the *p*-values of the unpaired t-test with two digits, with yellow font colour indicating values below 0.05, meaning that the variables under factual and counterfactual conditions differ significantly.
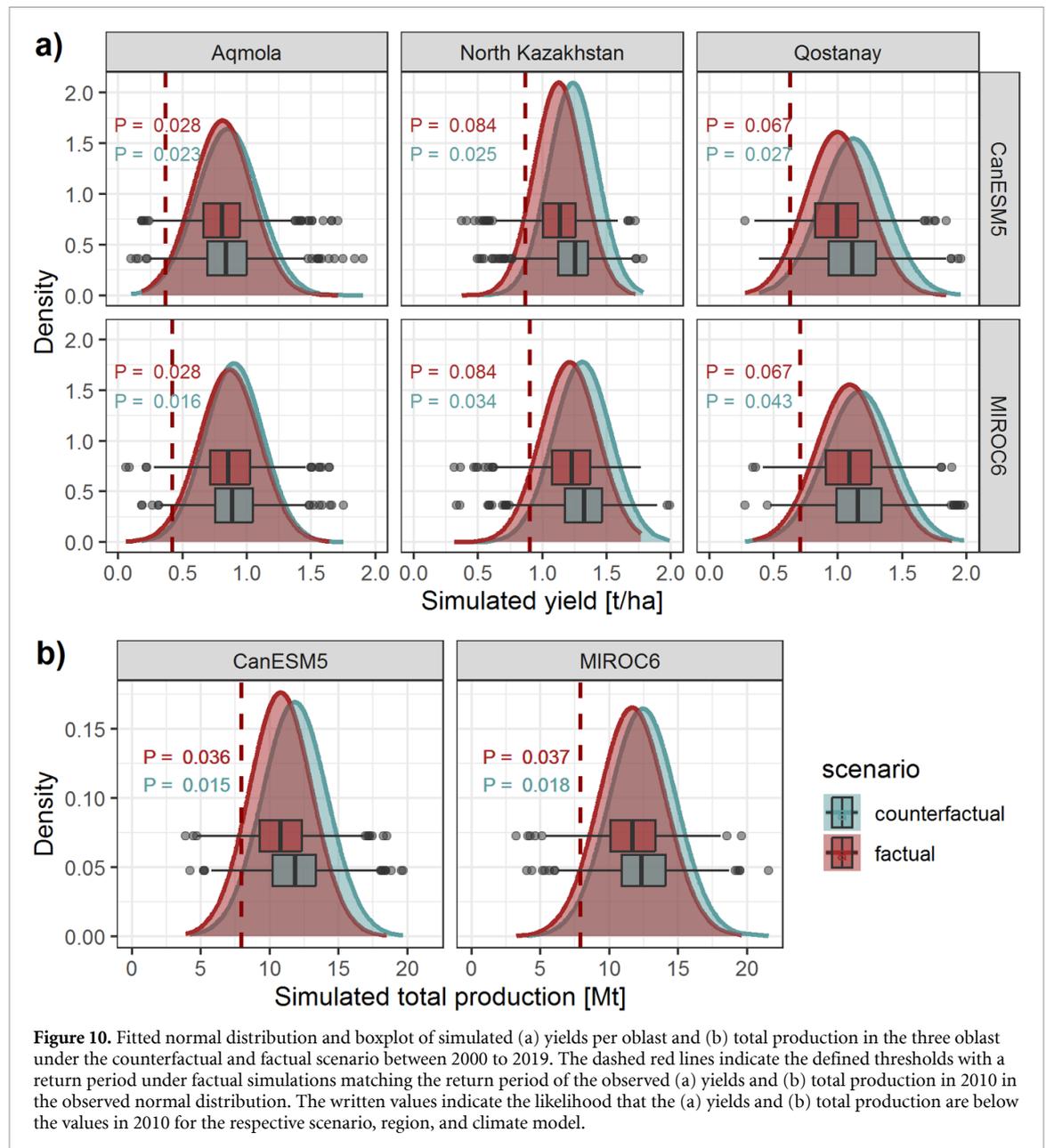
simulations (figure 11(a)). The sensitivity test, conducted by step-wise removal of one variable, results in small variations in the best estimates of the RRs, ranging from 1.7 to 2.6, for MIROC6, and a much wider range from 0.7 to 10.3 for CanESM5 (for details, see SI section 4, figure S2 and table S3).

Additionally, we calculated the RRs for the second-lowest production year, 2012, to test the results' robustness. This resulted in the best estimate for the RR of 2.1 under both climate models (for details, see SI section 5 and figure S3).

Quantifying the subsequent economic impact between 2000 and 2019 based on simulated yields and observed export prices resulted in an estimated average annual export loss of 119 million USD (best estimate; 10th to 90th confidence interval from 96 to 142 million USD) under MIROC6 simulations and of 158 million USD (135–180 million USD) under CanESM5 simulations (figure 11(b)).
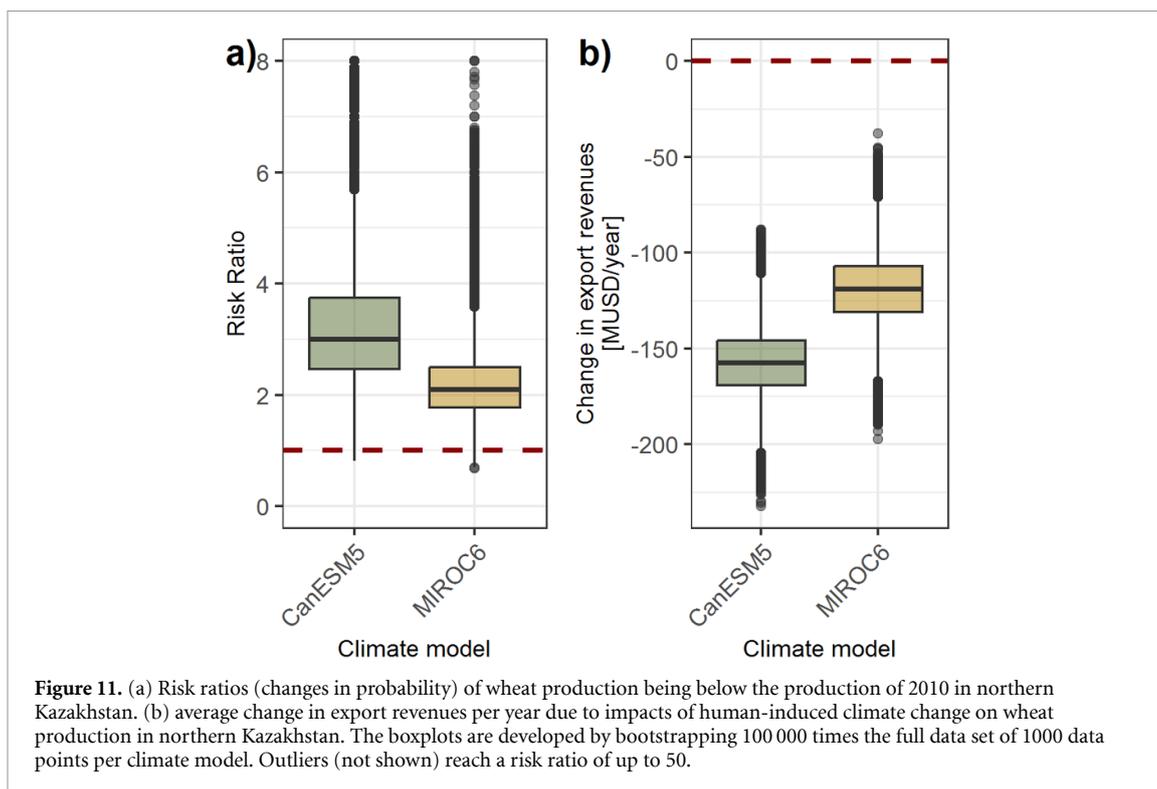
4. Discussion and conclusions

This study presents a climate impact attribution study for wheat production in northern Kazakhstan based on bias-adjusted counterfactual and factual climate model data from two large ensembles of latest-generation climate models as input to a statistical subnational yield model. We consider the statistical yield model as fit for purpose as it has a reasonably high R^2, the low yields in 2010 are accurately reproduced, the signs of the coefficients agree between the three models at the oblast level and between all models of the sensitivity test, and the model coefficients are physically meaningful. More precipitation and the absence of dry spells are associated with higher simulated yields which is consistent with previous studies (Pavlova *et al* 2014, Fehér *et al* 2016, Babkenov *et al* 2020, Shmelev *et al* 2021), which identify water scarcity as the primary stress factor for wheat in Kazakhstan. High daily-minimum temperatures have negative impacts on simulated yields as was also reported by Romanovska *et al* (2023). Our model suggests negative impacts of heat events on wheat whereby Schierhorn *et al* (2020) could not find this influence for northern Kazakhstan. The model indicates positive effects of high variability in the diurnal temperature range on yields, which is plausible due to its association with a higher variability in cloud cover that influences precipitation, temperatures, and solar radiation. The modelling exercise suggests insufficient GDDs not to be a clear limiting factor for spring wheat yields in northern Kazakhstan. Including this variable in the model, results in lower R^2 values in the out-of-sample validation compared to the main model used, and the model coefficients have opposite signs for different oblasts (not shown).

Figure 10. Fitted normal distribution and boxplot of simulated (a) yields per oblast and (b) total production in the three oblast under the counterfactual and factual scenario between 2000 to 2019. The dashed red lines indicate the defined thresholds with a return period under factual simulations matching the return period of the observed (a) yields and (b) total production in 2010 in the observed normal distribution. The written values indicate the likelihood that the (a) yields and (b) total production are below the values in 2010 for the respective scenario, region, and climate model.

We found that anthropogenic climate forcing has significantly increased all temperature-related variables considered, and has slightly increased precipitation between January and September, mainly driven by an increase from January to March. The study reveals that human-induced climate change had negative impacts on wheat production and the economy in northern Kazakhstan during the 21st century. These impacts are mainly driven by the increase in daily-minimum temperatures during the reproductive phase and the intensification of heat events during the growing season. Previous research in the region is sparse and has produced mixed results regarding the impact of human-induced climate change on wheat production in Central Asia (Bezner Kerr *et al* 2022).

In Kazakhstan, agriculture is one of the pivotal sectors in its economy. The negative impacts of human-induced climate change on wheat production identified have likely lowered the country's gross domestic product through a reduction in export quantity. A decline in production levels may have also led to an increase in food prices, particularly as climate conditions and crop failures in the wider KUR region show linkages. Rising food prices have serious consequences for Central Asians, as a large proportion of income is spent on food procurement. For example, in Tajikistan, three out of four households used the majority of their expenditure on food while the country received 95% of their wheat imports from Kazakhstan in 2021 (UNICEF 2018, OEC 2023).

We consider the attribution results fairly robust as the sensitivity tests confirm the negative impacts of human-induced climate change on wheat production. However, the study has several limitations.

Figure 11. (a) Risk ratios (changes in probability) of wheat production being below the production of 2010 in northern Kazakhstan. (b) average change in export revenues per year due to impacts of human-induced climate change on wheat production in northern Kazakhstan. The boxplots are developed by bootstrapping 100 000 times the full data set of 1000 data points per climate model. Outliers (not shown) reach a risk ratio of up to 50.

- The use of more than two climate models would increase confidence in the results. However, the chosen models cover the CMIP6 spread in terms of simulated warming very well (Forster *et al* 2021). The attribution results derived from CanESM5 may overestimate the negative influence of temperature increases as this climate model shows a too high temperature sensitivity to greenhouse gas emissions (Nijsse *et al* 2020). The climate sensitivity in MIROC6, on the other hand, is on the low end of what is assessed as likely by the IPCC (Forster *et al* 2021).

- The bias-adjustment method used here for the climate model data is established for impact modelling looking at future projections (e.g. Jägermeyr *et al* (2021). In terms of attribution studies, an earlier version of the method has been used with large-ensemble climate data by Perkins-Kirkpatrick *et al* (2022: figure 3) and with a very small subset of the DAMIP data (one ensemble member per model) by Pietroiusti *et al* (2024) and others. Nevertheless, further characterisation of the influence of the bias-adjustment on the event statistics should be the subject of future studies.

- The statistical yield model's out-of-sample run has an R^2 value between 0.48 and 0.63. The model is not trained to explain any non-weather related factors, so we do not aim for an R^2 value of 1. This is here also not necessary as the focus of the study is to isolate and quantify the weather/climate contribution. We assume that the model accounts for a large part of the weather-induced yield variability, but not all of it. Therefore, the model might also explain only part of the impact of human-induced climate change on wheat yields.

- The yield model does not directly include CO_2 fertilisation, which could have a positive impact on crop yields (Sommer *et al* 2013).

- Our assessment of weather-crop influences is based solely on a statistical model. However, the additional use of a process-based model would cover further relevant factors of wheat yields and allow a better process understanding, to be considered for future work.

- The estimation of economic losses are simple. We thereby assume prices are equal under counterfactual conditions as it is beyond the scope of this paper to simulate global and regional wheat prices and export rates in either scenario.

- The 119–158 million USD loss in export revenues serves as an upper bound, as we assume that all production losses manifest in export losses. We consider this assumption to be plausible, as Araujo-Enciso and Fellmann (2020) estimate that a 15% reduction in wheat production leads to a decrease in net wheat exports of more than 25%. Moreover, the total economic loss would reach similar figures if the assumption is not met, as production losses would result in a national economic impact in any case.

We found that human-induced climate change, and especially rising temperatures, drives an increase in the likelihood of low-production years, a decrease in average production, and economic losses in Kazakhstan.

Additionally, climate projections indicate that temperatures will continue to rise in northern Kazakhstan (Lee *et al* 2021, Golian *et al* 2023), further endangering the stability of wheat production. Minimising this risk is crucial to ensure regional and global food security. The negative impacts of human-induced climate change on wheat yields in northern Kazakhstan evidenced here therefore call for ambitious global mitigation efforts and regional adaptation measures that reduce temperatures in the field or adopt more heat-resistant crops.

Data availability statement

The datasets analysed during the current study are available from the ESGF (https://esgf-node.llnl.gov/projects/cmip6/), from ISIMIP (https://protocol.isimip.org/#31-climate-related-forcing), and at the Bureau of National Statistics of Kazakhstan (https://stat.gov.kz/official/industry/14/statistic/7).

The data cannot be made publicly available upon publication because the cost of preparing, depositing and hosting the data would be prohibitive within the terms of this research project. The data that support the findings of this study are available upon reasonable request from the authors.

Code availability

Code can be made available upon request.

Conflict of interest

The authors have no relevant financial or non-financial interests to disclose.

Authors contributions

Paula Romanovska: Conceptualisation, Methodology, Formal analysis, Data Curation, Writing—Original Draft, Writing—Review & Editing, Visualisation; **Sabine Undorf**: Conceptualisation, Methodology, Data Curation, Writing—Review & Editing, Supervision; **Bernhard Schauberger**: Conceptualisation, Methodology, Writing—Review & Editing, Supervision; **Aigerim Duisenbekova**: Formal analysis, Data Curation, Writing—Review & Editing; **Christoph Gornott**: Conceptualisation, Methodology, Writing—Review & Editing, Supervision, Funding acquisition;

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