# The impact of climate change on cereal yields: Statistical evidence from France

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**Abstract**

Climate change is predicted to reduce crop productivity in several world regions. A growing literature has examined climate change impacts on crop yields by statistically estimating the historical relationship between weather variables and yield and projecting it into predicted future climate. We estimate a flexible statistical model using panel data from France over the period 1950-2014 to investigate the impacts of climate change on winter wheat, winter barley, and spring barley yields. For winter crops, our model captures the differential impacts of weather on yield growth over cold (fall-winter) and warm (spring-summer) seasons. Temperatures above 33°C during the warm season appear harmful to all three crops. For winter crops, cold-season temperatures have a negligible effect on crop growth. Cereal yields are predicted to decline due to climate change under a wide range of climate models and emissions scenarios. Impacts are almost exclusively driven by increased heat exposure during the warm season. Under the most rapid warming scenario (RCP8.5) and holding growing areas constant, our model ensemble predicts a 16% decline in winter wheat yield, a 20% decline in winter barley yield, and a 42% decline in spring barley yield by the end of the century. Under this scenario, uncertainty stemming from climate model projections clearly dominates that stemming from the historically estimated climate-yield relationship. A comparison of our results with those from a recent study for Kansas wheat points to the critical role of local climatology on the marginal yield response to extreme temperature exposure.

The overall impact of climate change on human well-being will depend on the combination of natural resilience of ecosystems and adaptation measures taken by farmers and other stakeholders. Agriculture is expected to be one of the economic activities most impacted by climate change because weather is an essential input into agricultural production (Howden et al. 2007; Fisher et al. 2012). Wheat is the most widely grown crop in the world (Lobell et al. 2012) and the second largest calorie source behind maize (Roberts and Schlenker 2013). There is mounting evidence, notably from statistical yield models that estimate the weather- or climate-yield relationship from historical data, that climate change will negatively affect maize yields in key producing regions (Schlenker and Roberts 2009; Schlenker and Lobell 2010; Fisher et al. 2012; Ortiz-Bobea and Just 2013; Chen et al. 2015; Burke and Emerick 2015). In contrast, evidence regarding the effects of rising temperatures on wheat yields still relies heavily on process-based approaches (Asseng et al. 2015).

In this paper, we estimate a flexible statistical yield model using a long panel of historical yield and gridded weather data for French departments over the period 1950-2014. We focus on two crops from the Triticeae tribe, wheat and barley. According to the Food and Agriculture Organization, France was the fifth largest producer of wheat and the second largest producer of barley in the world over the period 2009-2013. Wheat occupies more than half of the cereal acreage in France, while barley occupies 18%. These crops are primarily rainfed.[1] While the vast majority of wheat is planted in the fall, barley is grown either as a winter or a spring crop.

Recent studies point to detrimental effects of rising temperatures on wheat yields in various world regions (Lobell et al. 2012; Moore and Lobell 2014; Tack et al. 2015; Asseng et al. 2015).[2] This study provides robust statistical evidence of negative effects of rising temperatures on wheat and barley yields in a temperate region. Our inference is based on the most flexible statistical yield model utilized so far. Following Schlenker and Roberts (2009), our regression analysis estimates the crop yield effects of marginal time exposure to a large number of temperature intervals, controlling for precipitation effects and imposing only moderate structure on the shape of the temperature-yield relationship. For winter crops, we estimate marginal impacts for both cold and warm seasons. We derive climate change impacts on crop yields under 18 climate model-emission scenario combinations.

## Results

To determine the effects of temperature exposure and precipitation on yield, we use panel regressions that control for department-specific unobservables (such as soils) and technological change. We control for department-level unobservables by including fixed effects and for gradual technological change by including region-specific quadratic time trends (mainland France has 96 departments and 22 regions). For winter crops, weather variables are disaggregated into cold (fall-winter) and warm (spring-summer) months. Our analysis indicates that high temperatures during warm months have historically been associated with decreased cereal yields. Consequently, we find significantly negative yield impacts of projected climate change across all models, scenarios, and horizons, relative to a situation with current climate. Because we exploit year-to-year variation in yield about a regional

[1] Data from the French Agricultural Census indicate that the rate of irrigated acreage for winter wheat grew from 0.3% to 2.5% between 2000 and 2010.

[2] The multi-model study by Asseng et al. (2015) focusses on low- or no-vernalization wheat varieties, that is, summer varieties. Winter varieties play an important role in global wheat supply, as they are grown in several key producing regions such as the US, Canada, France, and Russia.

trend and a department's own average yield to estimate the weather-yield relationship, our estimates represent short-run impacts that allow for limited adaptation.

*Wheat and Barley Exhibit Sharp Decreases in Yield Associated with Exposure to Temperatures Greater than 33°C during Warm months*

Fig. 1 displays results from two specifications of the historical relationship between warm-season temperature exposure and yield for winter wheat, winter barley, and spring barley.

The blue line depicts a step function such that the effect of marginal exposure to temperature on the logarithm of yield is constant within a 3°C temperature interval. The green line assumes that yield growth is an eight-degree polynomial function of temperature. A 95% confidence interval that allows for errors to be spatially correlated across proximal departments is shown for the polynomial specification in gray. (Confidence intervals for the step function are shown in *SI Appendix*, Section 3.) The horizontal axis shows temperature ranging from 0°to 38°C. The vertical axis measures the change in log yield, each value being interpreted as the percentage change in yield if 24 hours of freezing (below 0°C) exposure were replaced with exposure at the selected temperature, keeping the growing season constant. A histogram of the average warm-season temperature distribution is shown at the bottom of each graph.

For all three crops, temperature effects on yield growth during warm months appear to be driven by heat exposure. All graphs remain relatively flat until about 33°C, where the yield responses decline sharply. This damage threshold is in line with previous statistical evidence on Kansas wheat (Tack et al. 2015). Winter and spring barley yields experience dramatic declines at temperatures above this threshold, with marginal 24 hour-exposure impacts in excess of 14% of yield loss at 36°C and above. Spring barley appears more sensitive to extreme heat than winter barley, reflecting the fact that the spring variety is at an earlier phase of development, and perhaps less robust, when entering the warm months. Winter wheat appears less sensitive to heat than winter barley, although marginal impacts at high temperatures are clearly negative and statistically significant. The negative association between heat exposure and yield growth appears stable across geographical subsets (*SI Appendix*, Section 5) and precipitation-level subsets (*SI Appendix*, Section 6).

*Winter Crop Yields Appear Insensitive to the Distribution of Temperature During Cold Months*

Fig. 2 depicts the relationship between yield growth and marginal temperature exposure during cold months for winter wheat and winter barley. The figures represent the effect on yield growth of replacing 24 hours of exposure at a temperature of -12°C or below by exposure at a given temperature above that threshold. For both crops, estimates of marginal impacts are not statistically different from zero. *SI Appendix*, Section 9 shows yield effects differentiated across fall and winter months. Overall, results suggest that existing crop varieties are well suited to the relatively mild fall and winter temperatures of France, in that marginal exposure to either very low (below -12°C) or very high (above 21°C) temperatures during the cold season do not have large damaging effects on yields.

### *For All Three Crops, Yield Growth Decreases with Precipitation over the Entire Range of Department-level Average Historical Precipitation*

Our regression results imply that the effect of cumulative warm-season precipitation follows an inverted-U shape and that yield growth decreases with precipitation over the entire range of departmental-level average historical precipitation. For winter crops, yields also decrease with cumulative precipitation during fall and winter months.

Specifically, for winter wheat (resp. winter barley), the quadratic yield response function peaks at 124 mm (resp. 97 mm) of spring-summer precipitation and 0 mm (resp. 0 mm) of fall-winter precipitation in the step function specification, whereas department-level precipitation averages across the period range from 335 mm to 368 mm (resp. from 273 mm to 304 mm) during warm months and from 251 mm to 274 mm (resp. from 284 mm to 309 mm) during cold months. For spring barley, the peak occurs at 129 mm of spring-summer precipitation, whereas department-level average precipitation ranges from 305 mm to 338 mm. These findings clearly indicate that wheat and barley yields would increase in France with lower precipitation, *ceteris paribus*. They are also consistent with the very low rates of irrigation observed for wheat (2.5% across all departments according to the 2010 Agricultural Census), which contrast with the high irrigation rates for maize (40% across all departments in 2010).

### *Climate Trends over the Period 1951-2014 Are Estimated to Have Caused Yield Reductions of 0.11-0.16% per Year*

Our regression coefficient estimates are used together with climate trend regressions to isolate the impacts of trends in temperature and precipitation on cereal yields over the historical period. Department-level regressions of temperature exposure variables on a time trend reveal that in every department, climate has become warmer over the study period during the growing season. Trends in precipitation are less clear, with some departments experiencing increases and others decreases. By multiplying department-level trends in climate variables by the corresponding coefficients from the historical weather-yield regression, one obtains the *ceteris paribus* impacts of climate trends on yield growth. Overall, the production-weighted impact of climate trends over the study period has been -0.11% per year for winter wheat, -0.09% per year for winter barley, and -0.16% per year for spring barley.[3]

A cumulative measure of climate-trend impacts over the period 1951-2014 can also be obtained by multiplying regression coefficients by the difference in climate variables between the beginning of the period (1951-1960) and the end of the period (2005-2014) at the department level. Aggregating over departments using average production weights, climate trends are found to have caused *ceteris paribus* reductions in production of -5.0% for winter wheat, -4.5% for winter barley, and -7.6% for spring barley.

*Holding Growing Seasons and Areas Fixed, Climate Change Over the 21st Century is Predicted to Reduce Cereal Yields under a Range of Climate Scenarios and Models*

We predict *ceteris paribus* impacts of climate change using five climate models (CanESM2, HadGEM2-ES, CCSM4, GFDL-ESM2M, and NorESM1-M) and the four Representative Concentration Pathways developed by the IPCC (RCP2.6, RCP4.5, RCP6.0, and RCP8.5). The flexible estimation of the historical weather-yield relationship translates into negative and statistically significant climate change impacts for all three crops, under all climate models and climate scenarios, for both the medium term (2037-2065) and the long term (2071-2099). Yield predictions are depicted in Fig. 3. The least impacted crop is winter wheat, with predicted yield declines ranging from 2-9% across climate models and scenarios for the medium term. By the end of the century, wheat yields decline by a much larger percentage under the more rapid warming scenarios RCP6.0 and RCP8.5 (4-23%), yet declines are comparable to those observed for the mid-century period under the slowest warming scenario (RCP2.6).

Results for barley are consistent with the higher estimated heat sensitivity. For winter barley, yields are predicted to decline by 2-12% in the medium term across models and scenarios. In the long term, effects are more pronounced except under the slowest warming scenario. Under the most rapid warming scenario, yields are predicted to decline by 8-34% depending on the climate model. These impacts are magnified for spring barley, with yield declines ranging from 18-64% by the end of the century under the most rapid warming scenario.

[3]These figures are based on the step function specification.

*Negative Climate Change Impacts Are Driven Overwhelmingly by Increased Exposure to Heat During Warm Months*

The climate characteristics that contribute to our impact estimates are temperature exposure and precipitation during the warm season and, for winter crops, during the cold season. To decipher the contributions of each climate characteristic to overall impact, we construct counterfactual scenarios where only one characteristic is allowed to change between the reference and projection periods. *SI Appendix*, Section 4 shows that the major contribution to climate change impacts comes from increased exposure to extreme heat during warm months. Ignoring other changes in climatology barely changes the size and significance of the estimated impacts, while ignoring changes in warm-season temperature virtually annihilates all impacts.

*Climate Change Impact Uncertainty is Largely Driven by Climate Model Uncertainty*

For a given climate scenario and a given time horizon, uncertainty in climate change impact estimates arises from both the historical weather-yield relationship and the climate model considered. However, climate model uncertainty generally plays a much larger role in overall uncertainty, especially for the most rapid warming scenarios. Focussing on the step function specification, for winter wheat in the long term under scenario RCP8.5 the standard deviation of yield decline estimates across climate models is more than 7%, whereas the average econometric standard error on these estimates is less than 3%. For winter barley, these figures translate to 10% and 3%, respectively. For spring barley, they translate to 20% and 4%, respectively. Impacts in the medium term tell a similar story.

*Negative Climate Change Impacts Are Robust to Alternative Growing-Season Definitions*

For winter wheat, we explore shifting the warm-season window uniformly for all departments and also generate region-specific growing season windows based on the 2006 regional survey of cultural practices conducted by the French Ministry of Agriculture (Agreste 2006). For winter and spring barley, we explore alternative growing seasons windows that are the same for all departments. For winter crops, we also split the cold season into fall and winter months. *SI Appendix*, Section 8 shows that climate change impact estimates remain significantly negative.

*Current Technology Trends Could Mitigate Some of the Predicted Yield Reductions Attributed to Climate Change*

To predict the net impacts that climate change and technical change may have on crop production, we project the regional technological trends estimated on the historical period into the two climate change horizons under study. This approach assumes that technology trends would continue into the projected periods according to their historical trajectory. Detailed results for each crop, horizon, and climate model/warming scenario combination are reported in *SI Appendix*, Section 13. Under the combined effects of climate change and technical change, most production impacts become positive, except under more severe warming scenarios in the long term. For instance, winter wheat, winter barley, and spring barley yields are predicted to decline by 11%, 28%, and 61%, respectively, in scenario RCP8.5 under the HadGEM2-ES model.

*We Find No Evidence of Medium- to Long-Run Adaptation that Reduces Heat Sensitivity for Any of the Crops Under Study*

First, we re-estimate the weather-yield relationship on two subsamples of our data, 1951-1982 and 1983-2014. Results in *SI Appendix*, Section 7 indicate that the damaging effects of heat exposure during the warm season have persisted throughout the period. We also show that climate impact estimates are still significantly negative and of a comparable order of magnitude when inference is based on the recent period 1983-2014.

Second, our main statistical model exploits year-to-year variation in weather to delineate the climate-yield relationship, and as such it only allows for short-run adaptation to weather shocks. In order to allow for medium- to long-run adaptation to changes in climate, we regress the logarithm of eight-year department-level yield averages on eight-year climate variables, department fixed effects, and a set of quadratic trends that control for smooth technological change at the regional level.[4] This estimation strategy identifies the medium-to-long-run effect of climate on yield from department-level climate deviations from the regional quadratic trend, after accounting for each department's average yield. Because averaging over years considerably reduces our sample size, we only include two temperature intervals (time at 0-33°C and time above 33°C during the warm season) and warm-season precipitation as climate variables. We estimate this regression using both the eight-year averaged data and the yearly data. Climate adaptation, if present, would translate into a marginal impact of heat exposure on yield that is less negative for the eight-year averaged data than for the yearly data. Instead, for all three crops we find point estimates that are more negative with the averaged data, and considerably more noisy. We attribute this increased noisiness to the dramatic reduction in the conditional variation in heat exposure when averaging weather across years (see *SI Appendix*, Section 14).

[4] We are aware of the long-differences approach implemented by Burke and Emerick (2015) for U.S. maize and soybeans but the relatively small size of our cross-section does not allow us to follow their approach. We choose an eight-year window as it allows for an even split of the sample period into eight periods. We experimented with ten-year periods and obtained comparable results.

## Discussion

Agronomic studies emphasizing the relationship between a plant's environment and its physiological processes have so far dominated the agricultural climate change impact literature (Schlenker and Roberts 2009). As evidenced by the recent multi-model study in Asseng et al. (2015), this remark holds for wheat in particular: out of the 30 crop models that were part of the study, 29 were deterministic process-based simulation models, and only one was a statistical model. There are good reasons to rely on process-based simulation models as they incorporate important aspects of plant-growth theory and usually account for very detailed agricultural, soil, and weather inputs. They can also accommodate $CO_2$ fertilization effects. The attendant disadvantage however is that these models may entail a very large number of parameters that are often calibrated against limited data. Another criticism is that they usually take farm management decisions as exogenous, and that they may fail to account for the yield impacts of crop pests (Adams et al. 1990).

In contrast, the statistical approach to climate impact modeling takes a more agnostic perspective on the plant growth process. It relies on the flexibility of the functional specification combined with extensive observational data to reveal the underlying weather- or climate-yield relationship, allowing for endogenous adaptation and indirect effects such as pest pressure. Of course, the reliability of the statistical approach is only as good as the actual degree of flexibility of the model specification, which in practice has been limited by the size of available datasets. For instance, the well-cited study of U.S. maize, soybeans, and cotton by Schlenker and Roberts (2009) imposes some assumptions such as time separability of temperature effects (an assumption already embodied in the agronomic concept of degree days) or the exogenous definition of the relevant growing season. There are ways to alleviate concerns associated with these assumptions through extensive robustness checks, that are explored in Schlenker and Roberts (2009) as well as the present study. Another limitation of the statistical approach is that positive temperature anomalies may be operating as proxies for short dry spells not captured by seasonal precipitation variables, so temperature-driven damages on crop yields are implicitly assuming a fixed covariance between high temperature and drought in the projection period. However, with additional information on planting and harvesting dates, crop growth stages, and the future covariance of climate variables, these assumptions can even be relaxed (Berry et al. 2014).

Existing statistical yield studies on wheat include Lobell et al. (2012), van der Velde et al. (2012),Licker et al. (2013), Moore and Lobell (2014), Moore and Lobell (2015), and Tack et al. (2015). Of these, only the last one estimates the climate-yield relationship in a relatively flexible fashion, albeit on a set of experimental yields. Among wheat studies, our work is closely related to the contributions of Licker et al. (2013) and Tack et al. (2015). Licker et al. (2013) investigate wheat yields in a single region of France; our dataset is larger in both the cross-sectional and time-series dimensions, and we use a much more flexible statistical model of the weather-yield relationship.[5]

Our study differs from Tack et al. (2015) in its empirical setting (a temperate climate as opposed to Kansas climate), the nature of the data used (administrative yields and gridded weather data as opposed to experimental yields and location-specific weather data), the set of crops considered, and the model specification. Whereas they use a degree-day approach (which implies piecewise monotonicity of the yield-temperature relationship over relatively large temperature intervals), we adopt a more flexible model. Like them, we separate cold and warm seasons (in *SI Appendix*, Section 9, we split the cold season into two parts as they do in their study). Comparing our results to theirs reveals that the marginal effects of temperature exposure are dependent on location, likely through different baseline climates. Whereas Tack et al. (2015) find that marginal exposure to freezing temperatures have a large, negative impact on winter wheat yield, we do not find evidence of such an effect. One possible explanation is that the baseline levels of exposure to very cold winter temperatures are much lower in Western Europe than in Kansas and the marginal effects may be nonlinear across the exposure spectrum. As a result, in our setting the negative impact of rising temperatures on yield due to increased heat exposure is not being mitigated by decreased exposure to winter cold under warming scenarios.

In order to better compare our results with those of Tack et al. (2015) for Kansas, in *SI Appendix*, Section 12 we report climate change impacts for uniform temperature changes ranging from +1°C to +5°C. Despite the absence of a mitigating effect of increased temperatures on exposure to winter cold, our regression estimates imply less dramatic decreases in wheat yield, -15% versus about -50% at +5°C. We attribute this discrepancy to the difference in the estimated effect of heat exposure on yield growth. While our step function model implies a yield decline of -4.1% due to one-day exposure to 36°C, their model implies a decline of -15.2%.[6] One explanation as to why their estimate of the marginal effect of heat exposure on yield growth differs from ours, beyond differences in varietal traits, might be that Kansas climate is hotter than French climate during the warm season, and marginal effects might be nonlinear across the heat exposure spectrum. Warm-season heat degree days (defined as degree days above 34°C) average 0.20 in our sample, versus 0.93

[5] They use average minimum and maximum temperature across months. Schlenker and Roberts (2009) and Tack et al. (2015) have shown that capturing exposure to extreme temperatures is crucial and cannot be achieved by using averages.

[6] In addition, the magnitudes of their marginal yield declines increase linearly with temperature above 34°C due to the degree-day specification, whereas ours are capped above 36°C.

in theirs. Another factor might be the difference in precipitation: in France, warm-season precipitation averages 335 mm to 368 mm depending on the department, versus 91 mm to 267 mm in the Kansas study depending on the site.

Statistical studies in a European context include Moore and Lobell (2014) and Moore and Lobell (2015), which rely on a common statistical yield model whereby both weather and climate influence yield growth, allowing for the estimation of both short- and long-run impacts. However, their model specification essentially implies that yearly deviations from climate averages in temperature and precipitation necessarily lead to yield declines, an assumption that we clearly reject in our model for precipitation. We find that yields are declining in both cold- and warm-season precipitation for all three crops over the range of historical levels, implying that drier weather is beneficial to yield growth for the crops under study.

Our estimates of heat sensitivity and climate change impacts suggest that winter crops are more resistant to warming than spring-sown crops. As such, a possible pathway of adaptation could be shifting from spring to winter varieties. Indeed, our data show that the share of winter barley in total barley acreage in France has increased from 21% in the period 1951-1960 to about 69% in the period 2005-2014, suggesting that crop choice may be moving toward more robust varieties.

## Methods

### *Data*

Department-level yield and acreage data for continental France over the period 1950-2014 was gathered by the authors using printed and digital reports from the Statistical Office of the French Ministry of Agriculture. We removed the year 1956 from the estimation. This year was an outlier with an exceptionally cold winter that resulted in a very large decrease in winter crop acreage (minus 67% and minus 62% for winter wheat and winter barley, respectively, relative to the average of 1954, 1955, 1957, and 1958) as farmers replanted spring crops after the winter. For winter barley, many departments had no yield observations for that year. Because marginal temperature impacts may differ between mild and exceptionally harsh winters and 1956 weather is not representative of average winter conditions either in the reference climate or the projected climate, we prefer the specification that omits 1956. In *SI Appendix*, Section 11 we show that including 1956 in the historical regression leads to very similar climate impacts.

Historical climate data was obtained from the E-OBS dataset version 11.0 from the EU-FP6 project ENSEMBLES (http://ensembles-eu.metoffice.com) and the data providers in the ECA&D project (Haylock et al. 2008). The E-OBS dataset provides daily gridded temperature and precipitation data for Europe for 1950-2014 with a spatial resolution of 0.25 degrees (about 25 km). Exposure to each 1°C temperature interval was derived from the daily data by fitting a double-sine curve between the minimum and maximum temperature of consecutive days.

The gridded data was aggregated to department-level data by weighting each E-OBS grid by the amount of agricultural area it contains. The amount of agricultural area was derived from 100 m resolution land cover data from the CORINE land cover project developed by the European Environment Agency (Bossard et al. 2000). We averaged the amount of agricultural area over the observation years 1996, 2000, and 2006. The historical temperature distribution is summarized in *SI Appendix*, Section 2.

The climate change projections were derived for five GCMs and all available RCP scenarios. Projections were first computed for monthly temperature and precipitation based on the native GCM grid as the difference in climatology between 30-year projection and reference (1976-2005) periods. We subsequently downscaled to the E-OBS grids using the four nearest centroids of each GCM's native grid. Finally the downscaled projections were added to the historical gridded climate data and department-level projected data were obtained using agricultural area weights as previously mentioned.

*Regression Models*

To estimate the historical weather-yield relationship, we rely on a fixed-effects regression of the form:

$$y_{it} = \alpha_i + f_r(t) + \int_0^H \phi_{it}(h)g(h)dh + \mathbf{X}_{it}\boldsymbol{\beta} + \varepsilon_{it} \tag{1}$$

where the logarithm of yield $y_{it}$ in department $i$ and year $t$ is assumed to depend on a department fixed effect $\alpha_i$, a region-specific quadratic time trend $f_r(t)$, the distribution of temperature $\phi_{it}(h)$ over the warm growing season, and a vector $\mathbf{X}_{it}$ comprised of cumulative warm-season precipitation and its square. For winter crops, we add the same temperature and precipitation variables cumulated over fall and winter months. Because each department is assumed to have a time-invariant growing season, our model identifies the impact of replacing exposure at a given temperature by exposure at a different temperature. Our excluded temperature category for warm months is all temperatures below 0°C, hence the lower bound of zero on the integral in equation (1). Model parameters related to weather are the $\boldsymbol{\beta}$ coefficients and the parameters of the function $g$. The error terms $\varepsilon_{it}$ are assumed be uncorrelated across time but spatially correlated across departments. Standard errors are corrected for spatial correlation following the method of Conley (1999). Our preferred spatial weights matrix involves interactions with neighbors up to the third degree, with a geometric decay rate, but we show in *SI Appendix*, Section 10 that our results are robust to alternative specifications of the weight function.

We use two flexible specifications for the function $g$. The first specification is a step function with 3°C temperature intervals, which assumes a constant marginal impact of exposure within each interval but does not restrict impacts across intervals. The second specification is a flexible polynomial function estimated using exposure data aggregated at 1°C intervals.[7] Both specifications assume that the effect of exposure to a given temperature is constant across the (spring-summer) growing season. Temperatures greater than 36°C are assumed to have the same effect as 36°C. (There is very little exposure to these higher temperatures in our data.) In our preferred model, the growing season is the same for all departments; results using growing season windows that vary based on latitude are discussed in the *Results* section. We define the spring-summer growing season as March 1-August 15 for winter wheat, March 1-July 15 for winter barley, and March 1-July 31 for spring barley. We define the fall-winter growing season as November 1-February 28 for winter wheat and October 16-February 28 for winter barley.[8] The selection of growing season windows is based on the French 2006 regional survey of cultural practices (Agreste 2006).

The two specifications of the function $g$ lead to models that are linear in parameters. Denoting by $\mathbf{W}_{it}$ the matrix of transformed weather variables and by $\hat{\boldsymbol{\gamma}}$ the vector of associated parameter estimates, we estimate climate change impacts by computing predicted yields under the reference climatology $\bar{\mathbf{W}}_{i0}$ (defined as the average weather for the harvest years 1977-2005) and under counterfactual climatologies $\bar{\mathbf{W}}_{i1}$ for the medium term (harvest years 2037-2065) and the long term (harvest years 2071-2099). The production impact under a given climate model, emissions scenario, and time horizon is calculated as

$$\text{(2)} \qquad \text{impact} = \frac{\sum_i \bar{a}_{i0} e^{\alpha_i + \hat{f}_r(\bar{t}_0) + \bar{\mathbf{W}}_{i1}\hat{\boldsymbol{\gamma}}}}{\sum_i \bar{a}_{i0} e^{\alpha_i + \hat{f}_r(\bar{t}_0) + \bar{\mathbf{W}}_{i0}\hat{\boldsymbol{\gamma}}}} - 1$$

where $\bar{a}_{i0}$ represents the average crop acreage over the reference period and $\hat{f}_r(\bar{t}_0)$ is the estimated trend evaluated at the average of the reference period year index.

[7] The polynomial for the warm season is of degree 8; that for the cold season is of degree 9. To select polynomial degrees, we estimated polynomials of increasing order until the relationship between yield growth and temperature exposure appeared stable.

[8] February 29 is included in leap years. We include a dummy variable for leap years in regression (1) to account for the slightly longer growing season.

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**Figures:**

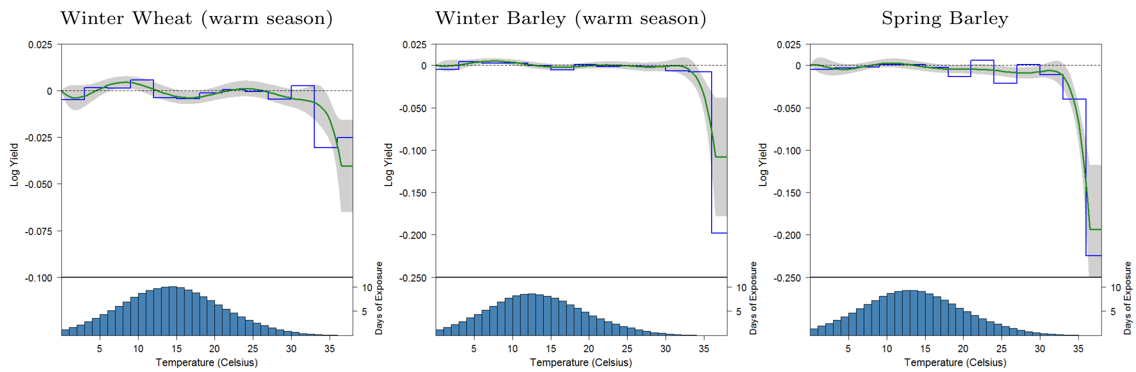


Figure 1: Historical temperature-yield relationships during the warm season. Graphs at the top of each frame represent changes in log yield if one day at below 0°C is replaced by one day at a given temperature. The 95% confidence interval for the polynomial regression accounts for spatial correlation. The scale on the vertical axis is different across crops. Histograms at the bottom of each frame show the average temperature distribution during the warm season.

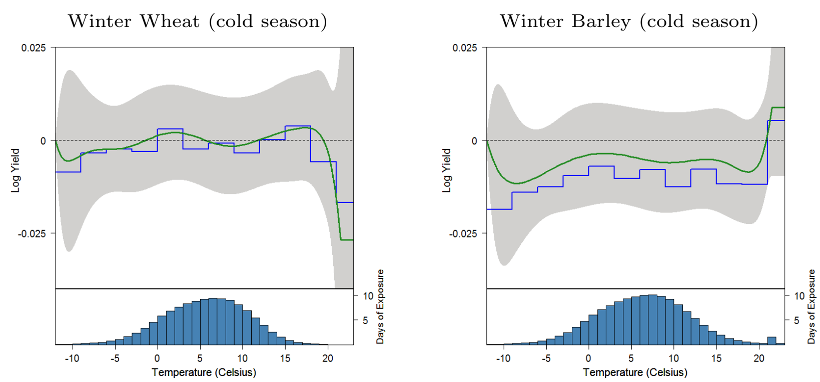


Figure 2: Historical temperature-yield relationships during the cold season. Graphs at the top of each frame represent changes in log yield if one day at below -12°C is replaced by one day at a given temperature. The 95% confidence interval for the polynomial regression accounts for spatial correlation. Histograms at the bottom of each frame show the average temperature distribution during the cold season.

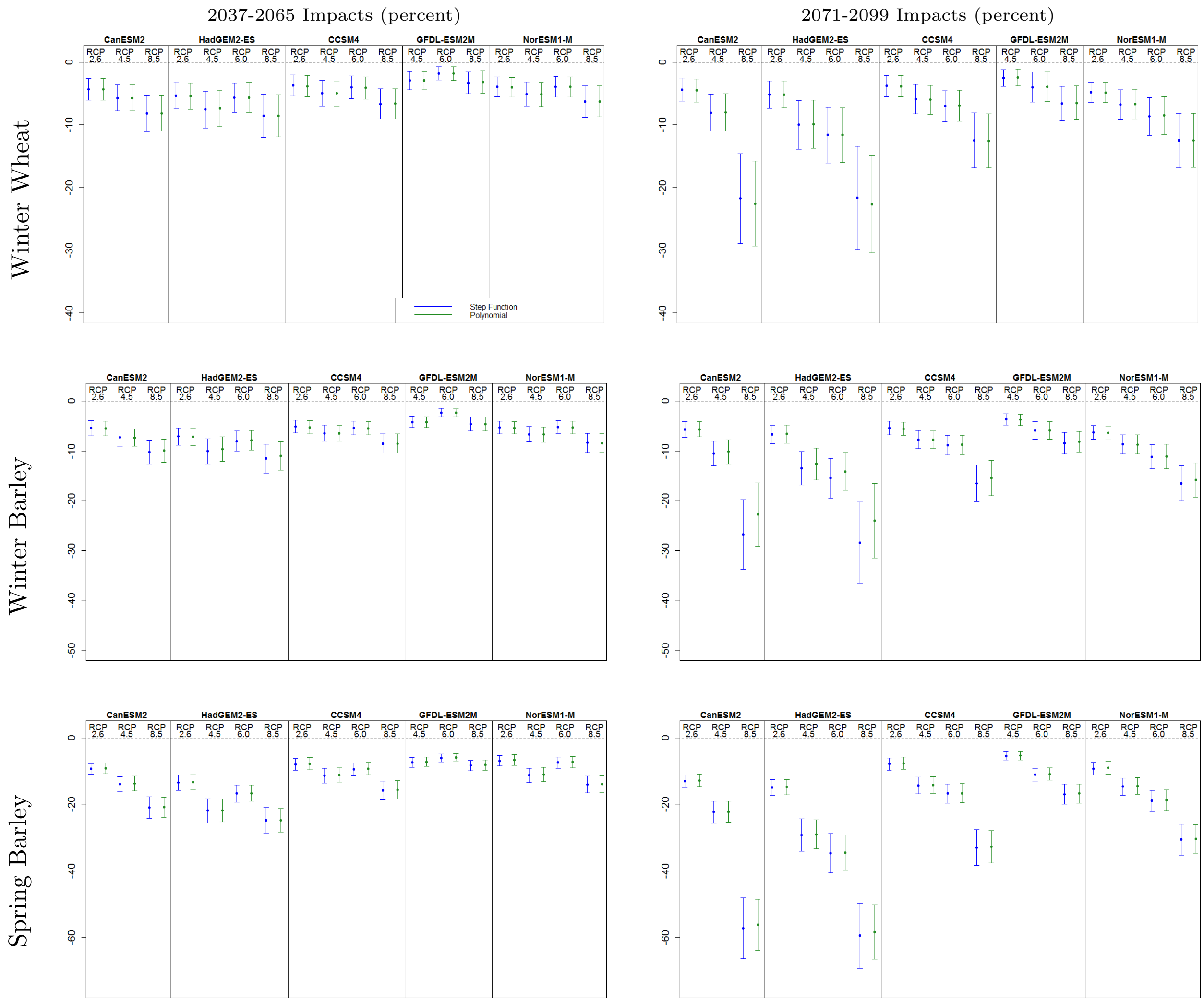


Figure 3: Climate change impacts on crop production under a variety of climate models and climate scenarios. Graphs display predicted changes in crop production, holding current growing areas constant, by the middle and the end of the century. Dots represent point estimates and whiskers show the 95% confidence interval that accounts for spatial correlation. The colors correspond to the yield specifications of Fig. 1. The scale on the vertical axis differs across crops.