LETTER

Negative impacts of climate change on cereal yields: statistical evidence from France

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Abstract

In several world regions, climate change is predicted to negatively affect crop productivity. The recent statistical yield literature emphasizes the importance of flexibly accounting for the distribution of growing-season temperature to better represent the effects of warming on crop yields. We estimate a flexible statistical yield model using a long panel from France to investigate the impacts of temperature and precipitation changes on wheat and barley yields. Winter varieties appear sensitive to extreme cold after planting. All yields respond negatively to an increase in spring–summer temperatures and are a decreasing function of precipitation about historical precipitation levels. Crop yields are predicted to be negatively affected by climate change under a wide range of climate models and emissions scenarios. Under warming scenario RCP8.5 and holding growing areas and technology constant, our model ensemble predicts a 21.0% decline in winter wheat yield, a 17.3% decline in winter barley yield, and a 33.6% decline in spring barley yield by the end of the century. Uncertainty from climate projections dominates uncertainty from the statistical model. Finally, our model predicts that continuing technology trends would counterbalance most of the effects of climate change.

1. Introduction

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 [1, 2]. Wheat is the most widely grown crop in the world [3] and the first source of calories ultimately delivered to humans as food, on par with rice [4]. 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 [2, 5–9]. In contrast, evidence regarding the effects of rising temperatures on wheat yields still relies heavily on process-based approaches [10–14]. Ref. [15] shows that the few available statistical estimates of the impacts of temperature on wheat yields are comparable to estimates from process-based models, globally and for key producing regions.5

In this paper, we estimate a flexible statistical yield model using a panel of historical yield and gridded weather data for French departments over the period 1950–2015. We study two crops of 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 2010–2014. Wheat occupies more than half of the cereal acreage in France, while barley occupies 18%.

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These crops are primarily rainfed.\textsuperscript{6} While the majority of wheat is planted in the fall, barley is grown either as a winter or a spring crop. The main paper focuses on the three major crops: winter wheat, winter barley, and spring barley. Throughout the supplementary data available at stacks.iop.org/ERL/12/054007/mmedia, we show additional results for spring wheat.\textsuperscript{7}

Recent studies point to detrimental effects of rising temperatures on wheat yields in various world regions, including Western Europe \cite{11, 3, 17, 18, 12, 15}. Perhaps surprisingly, recent simulations using the International Food Policy and Research Institute's IMPACT model predict that wheat yields will rise in Europe by 2050 under the effect of climate change \cite{13}. The present study provides the first evidence of negative effects of warming on wheat and barley yields in Western Europe based on a flexible statistical model.\textsuperscript{8} Following \cite{5}, our regression analysis estimates the crop yield effects of changes in time exposure to a large number of temperature intervals, controlling for non-monotonic precipitation effects and imposing only moderate structure on the shape of the temperature-yield relationship. For winter crops, we estimate separate marginal impacts for fall months, winter months, and the warm season (spring and summer months). Our panel regressions control for time-invariant department-specific unobservables (such as soils) and smooth technological change at the regional level. (Mainland France has 96 departments and 22 regions.) Following the recommendation of \cite{19}, we derive climate change impacts on crop yields under 18 climate model/emissions scenario combinations. Because we exploit year-to-year anomalies in yield about a regional trend and a department’s own average yield to identify the weather-yield relationship, our estimates represent short-run impacts that only allow for within-year adaptation.

2. Methods

Department-level yield and acreage data for continental France over the period 1950–2015 were gathered by the authors using print 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 dramatic decline in winter crop acreage as farmers replanted spring crops after the winter. 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 period or the projection periods, we prefer the specification that omits 1956. In online supplementary data, section 13 we show that including 1956 in the historical regression leads to similar climate change impacts.

Historical climate data were obtained from the E-OBS dataset version 14.0 from the EU–FP6 project ENSEMBLES (http://ensembles-eu.metoffice.com) and the data providers in the ECA&D project \cite{20}. The E-OBS dataset provides daily gridded temperature and precipitation data for Europe for 1950–2015 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 temperatures of consecutive days.

The gridded data were 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 \cite{21}. We averaged the amount of agricultural area over the observation years 1996, 2000, and 2006. The historical temperature distribution is summarized in section 2 of the online supplementary data.

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, following \cite{22}, 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.

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

\begin{equation}
\ln(y_{it}) = \alpha_i + f_r(t) + \int_0^H \phi(h)g(h)dh + X_{it} \beta + e_{it}
\end{equation}

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 $\phi(h)$ over the warm growing season, and a vector $X_{it}$ comprised of cumulative warm-season precipitation and its square. For winter crops, we add the same temperature and precipitation variables cumulated separately over fall months and winter months. Because the growing season is assumed to be time-invariant, 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

\textsuperscript{6} The French Agricultural Census indicates irrigation rates of 0.3% and 2.5% nationally for wheat in 2000 and 2010, respectively. Only a handful of departments show irrigation rates higher than 10%. Irrigation rates are likely to have been lower in the period before 2000. Figures are not available for barley, likely because irrigation rates are lower for that crop.

\textsuperscript{7} Spring wheat has not been grown consistently across French departments, and as a result the sample size is smaller for this crop.

\textsuperscript{8} The only statistical study we are aware of for this region is that by \cite{17}. Their statistical model is functionally restrictive compared to the models investigated here.
0°C, hence the lower bound of zero on the integral in equation (1). Model parameters related to weather are the $\beta$ coefficients and the parameters of the function $g$. The error terms $e_{it}$ are assumed be uncorrelated across years but spatially correlated across departments. Standard errors are corrected for spatial correlation following the method of [23]. Our preferred spatial weights matrix involves interactions with neighbors up to the third degree, with a geometric decay rate. We show in the online supplementary data, section 11 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 2°C temperature intervals, which assumes a constant marginal effect of exposure within each interval without restricting effects across intervals. The second specification is a flexible polynomial function estimated using exposure data aggregated over 1°C intervals. Both specifications assume that the effect of exposure to a given temperature is constant across the growing season. For the step (resp. polynomial) function, exposure to all temperatures above 32°C (resp. 33.5°C) are assumed to have the same marginal effect. (There is little exposure to temperatures above 34°C 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 online supplementary data, section 10. We define the spring–summer growing season as March 1–July 31 for winter wheat and spring barley, and March 1–July 15 for winter barley. The fall season is defined as November 1–December 31 for winter wheat and October 16–December 31 for winter barley. The winter season is defined as January 1–February 28. The selection of growing season windows is based on the French 2006 regional survey of cultural practices [24].

The two specifications of the function $g$ lead to models that are linear in parameters. Denoting by $W_{it}$ the matrix of transformed weather variables and by $\tilde{y}$ the vector of associated parameter estimates, we estimate climate change impacts by computing predicted yields under the reference climatology $\tilde{W}_0$ (defined as the average weather for the harvest years 1977–2005) and under counterfactual climatologies $\tilde{W}_t$ 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

$$\text{impact} = \frac{\sum_i \tilde{\pi}_i e^{g_i \tilde{y}_{i(t)} + \tilde{\alpha}_i}}{\sum_i \tilde{\pi}_i e^{g_i \tilde{y}_{i(t)} + \tilde{\alpha}_i}} - 1$$

where $\tilde{\pi}_i$ represents the average crop acreage over the reference period and $\tilde{\alpha}_i$ is the estimated trend evaluated at the average of the reference period year index.

3. Results

3.1. Yield responses to the distribution of temperature

Figure 1 displays results for 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 exposure to temperature on the logarithm of yield is constant within each 2°C temperature interval. The green line assumes that yield growth is a nine-degree polynomial function of temperature. A 95% confidence interval that allows for errors to be spatially correlated across proximal departments is shown in gray for the polynomial specification. (The confidence interval for the step function is shown in the online supplementary data, section 4.) The horizontal axis shows temperatures ranging from 0 to 36°C. The vertical axis measures the change in log yield, each

![Figure 1. Historical yield–temperature relationships during warm months. Graphs at the top of each frame represent changes in log yield if one day at 0°C or below is replaced by one day at a given temperature, holding the total number of days in the season constant. The 95% confidence interval for the polynomial regression is shown in gray and accounts for spatial correlation. Histograms at the bottom of each frame show the average temperature exposure across all departments and years in the sample.](image-url)
Figure 2. Historical yield–temperature relationships during fall months. Graphs at the top of each frame represent changes in log yield if one day at −6 °C or below is replaced by one day at a given temperature, holding the total number of days in the season constant. The 95% confidence interval for the polynomial regression is shown in gray and accounts for spatial correlation. Histograms at the bottom of each frame show the average temperature exposure across all departments and years in the sample.

The story is much different for spring barley, which exhibits an overall mild decline in yield (relative to freezing) for temperatures in the range 16 °C–30 °C, followed by a very sharp decline for temperatures above 32 °C (−4.6% relative to freezing in the step function specification), indicating a negative association between heat and yield. Experimental evidence suggests that heat exposure from the stage of panicle differentiation until meiosis of pollen mother cells can negatively affect reproductive growth by abolishing seed fertility [27, 28].

Figure 2 depicts the relationship between yield growth and marginal temperature exposure during fall months, for winter wheat and winter barley. The figures represent the impact on yield growth of replacing one day of exposure at a temperature of −6 °C or below by one day of exposure at a given temperature above that threshold. Estimates of marginal impacts are positive and statistically different from zero for most temperature intervals, particularly for winter barley. These results suggest that extreme cold can be damaging during fall months. Section 4 of the online supplementary data shows yield response curves for winter months. For both crops, exposure to most temperature intervals does not have a significantly different effect relative to exposure to temperatures below −6 °C, suggesting an absence of sensitivity to the temperature distribution during winter months, at least within the range observed in our sample. These findings seem consistent with the concept of cold acclimation (or cold hardening), a period during which gradual exposure to cooler temperatures after the plant has emerged allows seedlings to develop resistance to cold. As such, exposure to very cold temperatures is believed to be damaging when it occurs early in the season.12 These

value being interpreted as the percentage change in yield if 24 h of freezing (below 0 °C) exposure were replaced with exposure at the selected temperature, keeping the growing season and the rest of the temperature distribution constant.11 A histogram of the average warm-season temperature distribution is shown at the bottom of each graph.

For winter wheat, the yield response exhibits a positive and significant effect of exposure to cool temperatures (7 °C–11 °C according to the polynomial; 10 °C–12 °C according to the step function) relative to freezing. Such effect is absent for warmer temperatures in the range of 12 °C–31 °C. Temperatures above 32 °C have a significantly negative effect on yield growth compared to freezing, suggesting heat sensitivity. The step function specification indicates that a one-day exposure above 32 °C would cause a 2.9% decrease in yield relative to freezing. These findings appear consistent with the meta-analysis by [25] regarding the effects of temperature exposure on wheat development. The authors report an optimal temperature during the critical phenological stage of terminal spikelet initiation of about 11 °C, which our estimated peak could be reflecting. The authors also report that temperatures above 31 °C can induce pollen sterility immediately before anthesis [26].

For winter barley, we find qualitatively similar but more muted effects of temperature exposure on yield. The yield response shows a small, positive effect of cool temperatures between 6 and 9 °C in the polynomial specification, as well as a negative effect of temperatures above 33 °C. In the step function specification, only the negative effect of heat is statistically significant.

11 Unlike [5], we choose not to shift curves so that the exposure-weighted impact is zero. This allows us not only to compare marginal exposure effects between any two positive temperature intervals (by measuring the vertical difference), but also to evaluate marginal exposure effects at any positive temperature relative to freezing (by simply looking at the ordinate).

12 The organization ARVALIS indicates that the temperature threshold below which damaging effects occur in un-hardened cereals is −6 °C (www.arvalis-infos.fr/l-endurcissement-determine-la-tolerance-au-gel-des-cereales-@/view-17790-arvarticle.html).
results are also consistent with the vernalization requirements of winter varieties. According to the applied agricultural research organization ARVALIS, typical varieties used in France require between 45 and 60 d of vernalization. These requirements are usually met over fall and winter months, therefore it is not surprising that we find no significant effects of marginal changes in the temperature distribution during winter months.

Consistent with recent statistical studies performed in other settings [5, 18], the choice of a flexible specification of growing-season temperature exposure significantly improves out-of-sample prediction performance relative to a model that uses average temperature. Section 5 of the online supplementary data shows model comparisons based on the root-mean-square error of out-of-sample predictions. We compare the two flexible specifications discussed above with two models: (i) a ‘naïve’ model that does not include any weather variables, and (ii) a model that uses growing-season average temperature and its square (separated across fall, winter, and warm months for winter crops) to capture temperature exposure. For each replication (1000 total), each model is trained on a random sample of about 85% of observations and tested on the remaining 15%. To account for spatial correlation across observations, we sample region-years instead of department-years. Pairwise comparisons using the Welch t-test show that models with weather variables perform significantly better than the naïve model. The step function and polynomial specifications perform significantly better than the model with average temperature variables, and these flexible specifications perform equally well relative to each other.

3.2. Yield responses to precipitation
Our regression results imply that the effect of cumulative warm-season precipitation follows an inverted-U shape and that yield typically decreases with 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 206 mm (resp. 200 mm) of spring-summer precipitation and is decreasing in fall and winter precipitation.14 Across departments, warm-season precipitation averages for winter wheat (resp. winter barley) range from 199 mm to 455 mm (resp. 191 mm to 415 mm), with 1 (resp. 2) departments having averages below the estimated peak. For spring barley, the peak occurs at 236 mm of spring–summer precipitation, with the average precipitation lying above this value in 84 out of 88 departments. (Spring barley has the same warm-season definition as winter wheat and thus the same range of department-level precipitation averages.) The few departments with historical precipitation below the optimum are located along the Mediterranean coast.

These findings 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—0.3% (resp. 2.5%) across all departments according to the 2000 (resp. 2010) French Agricultural Census—which contrast with the high irrigation rates for maize (44.5% and 40%, respectively).15

3.3. Climate change impacts
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). All models and scenarios show positive warming trends for all departments, while precipitation trends are less clear. The flexible estimation of the historical weather-yield relationship translates into negative and statistically significant predicted 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). Predicted yield impacts relative to the period 1977–2005 are depicted in figure 3. Winter wheat and winter barley appear less affected, with similar yield declines. In the medium term, projected yield declines range from 3.5% to 12.9% for winter wheat (2.3% to 12.1% for winter barley) across climate models and scenarios. By the end of the century, winter wheat (resp. winter barley) yields are predicted to decline by an average of 17.2% (resp. 14.6%) under the more rapid warming scenarios RCP6.0 and RCP8.5, yet under the slowest warming scenario (RCP2.6) declines are comparable to those observed for the mid-century period.

Results for spring barley are consistent with its higher estimated heat sensitivity. Yield is predicted to decline by 7.0%–25.2% 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, yield is predicted to decline by 16.7%–45.8% depending on the climate model.

Sections 7 and 8 of the online supplementary data show that the negative impact predictions are robust to estimating the weather-yield relationship on alternative geographical (North and South) and temporal (1983–2015) data subsets. Section 9 further shows that our predictions are robust to estimation on subsets of

13 See www.arvalis-infos.fr/la-vernalisation-un-passage-oblige-pour-fleurn@view-17789-arvarticle.html.
14 These values refer to the polynomial; values for the step function are extremely close.

15 Our findings are also corroborated by the sharp decline in wheat yields observed in 2016, which has been attributed, in part, to wet conditions during the spring. See, for instance, www.france24.com/en/20160809french-wheat-harvest-catastrophic-30yearlow-economy-agriculture.
departments with varying precipitation levels and to the inclusion of a heat exposure-precipitation interaction in the regression model. These results suggest that the potentially beneficial effects of precipitation on heat stress would do little to mitigate the negative impacts of warming.\textsuperscript{16} Consistent with these negative impacts, section 16 of the online supplementary data shows how weather trends over the historical period have resulted in cereal yield losses ranging from \(-0.10\%\) per year for winter barley to \(-0.22\%\) per year for spring barley.

The climate characteristics that contribute to our impact estimates are temperature exposure and precipitation during warm months and, for winter crops, during fall and winter months. To decipher the contributions of each climate characteristic to overall impact, in section 6 of the online supplementary data we construct counterfactual scenarios where only one characteristic is allowed to change between the reference and projection periods. These counterfactuals show that net impacts cannot be explained without accounting for changes in warm-season temperature. In contrast, ignoring other changes in climatology leads to counterfactual impacts that are very close to the net impacts. Therefore, net impacts are primarily driven by changes in warm-season temperature exposure.\textsuperscript{17}

To better understand how changes in the distribution of warm-season temperature translate into negative climate change impacts, in figure 4 we isolate the impacts of changes in exposure to each 2°C interval based on the polynomial specification, assuming a uniform shift of the whole temperature distribution by +3°C. The negative impacts for winter wheat and winter barley appear to be jointly driven by decreased exposure to beneficial, cool temperatures (below 12°C) and increased exposure to detrimental, higher temperatures, although the relative contributions of these factors are crop-dependent. Negative warming impacts for spring barley are driven by increased exposure to temperatures above 16°C.

\textsuperscript{16} Section 12 of the online supplementary data also shows that climate change impacts are robust to the removal from the estimation sample of a subset of departments identified as more prone to irrigation towards the end of our time period.

\textsuperscript{17} For winter crops, changes in fall and winter temperatures also result in statistically significant yield effects. However, these effects are smaller in magnitude than those due to warm-season temperature, and they cancel each other out, the positive effects of warming during fall months being offset by negative effects during winter months.
For given climate scenario and time horizon, uncertainty in climate change impact estimates arises from both the historical weather-yield relationship and the climate model considered, as evidenced in figure 3. Climate model uncertainty generally plays a much larger role in overall uncertainty, especially for the most rapid warming scenarios. Focusing on the polynomial specification for winter wheat in the long term and under scenario RCP8.5, the standard deviation of estimates of yield decline across climate models is 7.6%, whereas the average econometric standard error on these estimates is 2.0%. For winter barley, these figures translate to 4.9% and 1.8%, respectively. For spring barley, they translate to 12.1% and 2.2%, respectively. Impacts in the medium term tell a similar story.

3.4. Net impacts with secular technological progress
Fitted historical technology trends generally imply secular yield increases much larger than the yield decreases implied by climate projections about the yield trend. For instance, over the reference period 1977–2005, yield increases attributable to technology trends averaged 1.69% (resp. 1.68%, resp. 1.61%) per year across French departments for winter wheat (resp. winter barley, resp. spring barley). In comparison, under scenario RCP8.5 in the long term, the HadGEM2-ES model implies yield declines of about 9.1% (resp. 11.7%; resp. 10.4%) for winter wheat (resp. winter barley; resp. spring barley).

Agronomic studies emphasizing the relationship between a plant's environment and its physiological processes have so far dominated the agricultural climate change impact literature. As evidenced by the recent multi-model study in [12], this remark holds for wheat in particular: out of the 30 crop models considered, 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 explicitly incorporate important aspects of plant-growth theory (e.g. vernalization requirements) and usually account for very detailed agricultural, soil, and weather inputs. They can also accommodate CO2 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.

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

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18 These figures are based on the fitted regional trends in the historical panel regression.
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 US maize, soybeans, and cotton [5] imposes some assumptions such as time separability of temperature effects 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 [5] as well as the present study. With information on planting and harvesting dates and crop growth stages, these assumptions can even be relaxed [31, 32]. 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 [33, 34] so temperature-driven damages on crop yields are implicitly assuming a fixed covariance between high temperature and drought in the projection period. Additional information on historical soil moisture levels throughout the growing season would be needed to fully allay this concern. In addition, a better understanding is needed in terms of the causal effect of high temperature on drought and the effect of drought on high temperature.

Existing statistical yield studies on wheat include [3, 16–18, 35–37]. Of these, only [18] estimates the climate–yield relationship in a relatively flexible fashion. Our study differs from [18] in its empirical setting (a temperate climate as opposed to the Kansas climate), the nature of the data used (administrative yields and grided weather data as opposed to experimental yields and field-specific weather data), the set of crops considered, and the model specification. While [18] uses a degree-day approach—which implies piecewise monotonicity of the yield–temperature relationship over relatively large temperature intervals—we adopt a more agnostic modeling approach. Comparing our results to theirs reveals similarities but also notable differences. Ref. [18] finds that marginal exposure to freezing (below 0 °C) temperatures have a large, negative impact on winter wheat yield during fall months. We also find negative effects of exposure to cold, but only for temperatures below −6 °C, and our estimated effect is almost an order of magnitude smaller. As a result, in our setting the negative impact of rising temperatures on yield due to increased heat exposure cannot be mitigated to the same extent by decreased exposure to cold during fall months. In order to better compare our results with those of [18] for Kansas, in the online supplementary data, section 14 we report climate change impacts for uniform temperature changes ranging from +1 °C to +5 °C. Our regression estimates imply much less dramatic decreases in wheat yield, −24% versus about −50% at +5 °C. We attribute this discrepancy to the difference in the estimated marginal effect of temperature exposure on yield growth during the warm season. The yield response to warm-season temperature exposure in [18] exhibits an almost flat portion for temperatures between 0 and 34 °C, followed by a sharp decline (with a marginal yield effect of one-day exposure to 35 °C equal to −7.6%). In France, we find beneficial effects of marginal exposure to cool temperatures, and our estimated effect of heat exposure is less negative (−2.9% for one-day exposure to 32 °C or above). However, given the minimal historical exposure to temperatures above 34 °C in France, one should be cautious in interpreting differences in heat sensitivity across the two locations.

Even if the underlying relationship between weather and crop yield were the same in Kansas and France, estimated marginal impacts might still differ due to differences in baseline climates as they might be approximating this relationship at different points across the heat exposure spectrum. The Kansas climate is hotter than French climate during the warm season. Warm-season heat degree days (defined in the Kansas study as degree days above 34 °C) average 0.24 in our sample, versus 0.93 for Kansas. This is despite the warm-season ending in July (France) compared to May (Kansas). Another factor might be the difference in precipitation: in France, warm-season precipitation averages 199 mm to 455 mm depending on the department, versus 91 mm to 267 mm in the Kansas study depending on the site. Finally, the smaller estimated impact of heat on wheat yield could partly be the result of attenuation bias arising from the use of department-aggregated weather data, rather than site-specific data as in [18]. This factor could also explain the smaller effect of freezing temperatures during fall months found in the present study.

Statistical studies in a European context include [17] and [37], which rely on a common statistical yield model whereby both weather and climate influence yield growth, allowing for the simultaneous estimation of short- and long-run impacts. However, their model specification implies that yearly deviations from climate averages in temperature and precipitation necessarily lead to yield declines, an assumption contradicted by our results. We find that yields are generally declining in precipitation over the relevant range, implying that drier weather would be beneficial to yield growth for the crops under study.21

Finally, our estimates of heat sensitivity and climate change impacts suggest that winter barley is more resistant to warming than spring barley. 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 70% in the period 2006–2015, indicating that crop choice may be moving toward more robust varieties. The authors would like to thank, without implication, Maximilian Auffhammer, Philippe Ciais, Dalia Ghanem, Wolfram Schlenker, Aaron Smith, two anonymous referees, as well as seminar participants at Purdue University and the 2016 AAEA meetings in Boston. We also thank Matthieu Stigler for helpful research assistantship and government staff in the French Ministry of Agriculture for facilitating access to agricultural data.

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