LETTERS
PUBLISHED ONLINE: 18 MAY 2014 | DOI: 10.1038/NCLIMATE2228
nature climate change

Adaptation potential of European agriculture in response to climate change

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Projecting the impacts of climate change on agriculture requires knowing or assuming how farmers will adapt. However, empirical estimates of the effectiveness of this private adaptation are scarce and the sensitivity of impact assessments to adaptation assumptions is not well understood[1,2]. Here we assess the potential effectiveness of private farmer adaptation in Europe by jointly estimating both short-run and long-run response functions using time-series and cross-sectional variation in subnational yield and profit data. The difference between the impacts of climate change projected using the short-run (limited adaptation) and long-run (substantial adaptation) response curves can be interpreted as the private adaptation potential. We find high adaptation potential for maize to future warming but large negative effects and only limited adaptation potential for wheat and barley. Overall, agricultural profits could increase slightly under climate change if farmers adapt but could decrease in many areas if there is no adaptation. Decomposing the variance in 2040 projected yields and farm profits using an ensemble of 13 climate model runs, we find that the rate at which farmers will adapt to rising temperatures is an important source of uncertainty.

Determining the overall effectiveness of adaptation solutions in agriculture is challenging because it is impossible to accurately enumerate and model all economically feasible options. Further, the rate at which farmers will adopt these options in response to climate change remains uncertain[1–3]. As a result, the sensitivity of existing impact projections to assumptions of private farmer adaptation is not well understood.

One promising approach to assess the potential of private adaptation in agriculture is to use past observations to simultaneously estimate two relationships between farm profits or yields and climate variables. The first is the long-term, equilibrium relationship based on cross-sectional variation in climate. Under the assumption that farmers have adjusted over the long-run to take full advantage of the climate they face, this response function captures the impacts from climate change if farmers are able to fully adapt using the set of available technologies[4]. The other is a short-term relationship based on interannual weather variation. As these weather shocks are transient and partially unanticipated, farmers can mitigate their effects only with a much more limited set of management options. Therefore, this response function gives the impacts from climate change if farmers are unable to implement long-run adaptations and instead respond to climate change as though it were simply unusual weather. Climate change impact projections made using these two response functions can be used to characterize the spread in impact projections resulting from uncertainty over how quickly farmers will adopt adaptive technologies and management practices already in use elsewhere[5,6].

Here we apply this approach to data from Europe, and then estimate the impact of future temperature and precipitation changes on yields and farm profits with and without adaptation. We estimate equation (1) separately for each dependent variable (farm profits and the yields of five major crops) using balanced panel data sets (Methods). Figure 1 shows the results graphically.

The long-run relationship between profits or yields and temperature is estimated using cross-sectional variation. We find a moderate relationship between farm profits and mean temperature, with maximum profits at growing season temperatures of 16.4 °C corresponding to parts of northern Spain or Italy. Wheat and barley show strong negative responses to warming across almost the entire range of climates in the study region whereas maize shows a much flatter response curve. Oilseed and sugarbeet yields both decline with higher temperatures over most of the study region, although the parameters of the oilseed yield regression are not accurately estimated. Precipitation response curves as well as the regression coefficients and standard errors for the preferred specification and a number of alternative robustness checks are presented and discussed in the Supplementary Information.

In all cases, the coefficient on the temperature deviation term ((Temp–Mean Temp)^2) is negative, indicating that there is a penalty associated with having a growing season that is cooler or warmer than the expected temperature. In other words, when the weather is different from expectation in a particular season, it imposes a cost in terms of profitability or yields lost as a result of management practices that turn out to be, *ex post*, imperfectly adjusted to the actual weather. The value of this coefficient is fairly large: a year that is one standard deviation (2.7 °C) warmer or cooler than average causes a decline in profitability of 9.7% and yield declines of between 6.1% (wheat yield) and 10.9% (maize yield) compared with what would have occurred if those temperatures were anticipated *ex ante*.

We estimate the impacts of climate change with and without adaptation by combining the long-run (excluding the penalty term) and short-run (including the penalty term) response curves respectively with an ensemble of 13 climate model runs[7] (Methods, Supplementary Fig. 2). These projections are conditional on assuming that land continues to be used in agriculture if profits are the dependent variable or in a particular crop if yields are the dependent variable (Supplementary Table 1). In general, projected temperature effects on yields for 2040 (2030–2049 average) relative to the 1975 (1960–1989 average) baseline are negative (Fig. 2a). Wheat and barley are highly sensitive to temperature, with the average 2 °C warming projected for 2040 resulting in yield reductions of 15–30% relative to what they would otherwise be.

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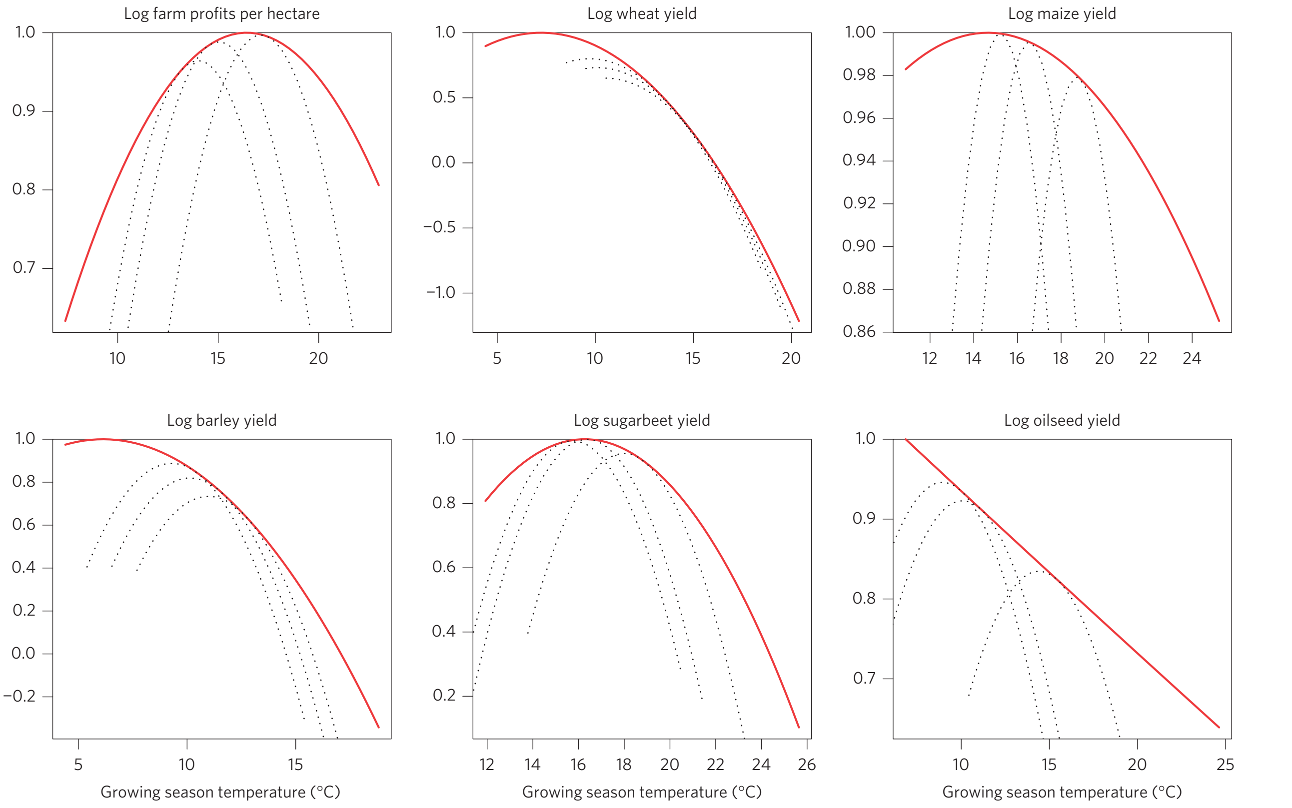

Figure 1 | Short- and long-run temperature response curves. Graphical depiction of the long-run (red solid lines) and short-run (black dotted lines) relationship between farm profits or yields and growing season temperature (°C) estimated using equation (1) (first specification, column one in Supplementary Table 3). The range of the *x* axis corresponds to the range of growing season temperature in each panel data set. The three examples of short-run relationships are plotted centred at the 25th, 50th and 75th percentiles of growing-season temperature. Curves are shifted along the *y* axis so that the maximum value over the plotting range is 1. As the dependent variable is logged, movement along the *y* axis represents a percentage change in the outcome variable.

Maize, sugarbeet and oilseed yields are more moderately impacted, primarily as a result of smaller estimated sensitivity to temperature over the range of growing season conditions in Europe. These long-run impact estimates are based on cross-sectional variation and so may be particularly vulnerable to omitted-variable bias. We believe equation (1) controls for major sources of bias but also note that a previous study reported very similar maize- and wheat-yield response curves using cross-sectional variation in a higher-resolution version of the same data set[8]. As they were able to include subnational fixed effects, the similarity between our results suggests that omitted variables are not substantially influencing our results, at least for wheat and maize yields.

The difference between the light and dark bars measures the potential for private farmer adaptation to reduce the negative effects of climate change. This potential is moderate but still important. For instance, barley yields are projected to decline by 22% but this loss could be cut to 15% with adaptation. The largest potential for adaptation relative to the size of overall impact is for maize yields. Without adaptation, losses from warming are projected to be 9% but adaptation has the potential to cut this to just over 1%.

Under climate change, average farm profits across Europe would increase modestly (1.5%) with adaptation but could decline by 2.3% without adaptation. (The impacts on profits differ from the yield impacts because the five crops studied here constitute only 25% of farm production value.) The long-run profit response curve is nonlinear, meaning the effect of warming varies with baseline climate and is geographically heterogeneous. Figure 2b shows the projected change in farm profits both with and without adaptation (right and left panels, respectively). If farmers are able to adapt effectively, then much of Europe should see small gains in profits. However, warmer regions in southern France, Spain, Italy, Greece and Portugal already beyond the temperature optimum of 16 °C could see substantial residual damages from climate change of over 10% even after adaptation. Adaptation is clearly important for moderating the effect of climate change on agricultural production. Without it, even cooler regions in central France and Germany could see declines in profitability due to warming by 2040.

The variance in our projections of the impacts of climate change on farm profits and yields are decomposed into three types of uncertainty: climate, response and adaptation uncertainty (Methods). Climate uncertainty results from uncertainty in future temperature and precipitation changes and is captured by the spread of climate model projections in the ensemble. Response uncertainty arises because we are unsure exactly how profits and yields will respond to a given change in temperature or precipitation and it depends on the precision of the estimates of the response function parameter. Adaptation uncertainty results from the fact that the rate of private farmer adaptation is uncertain and depends on the difference in projections made using the long- and short-run response functions.

Uncertainty around how well farmers will adapt to temperature impacts is an important source of variability (Fig. 3). For maize and sugarbeet yields it is the dominant uncertainty component. Moreover, for all variables except wheat and barley yields, the combination of adaptation and response uncertainty is larger than that from climate model projections. This means that ensembles of climate model output alone are inadequate to fully characterize the uncertainty in projections of the impact of climate change on agricultural production. Uncertainty resulting from an imperfectly

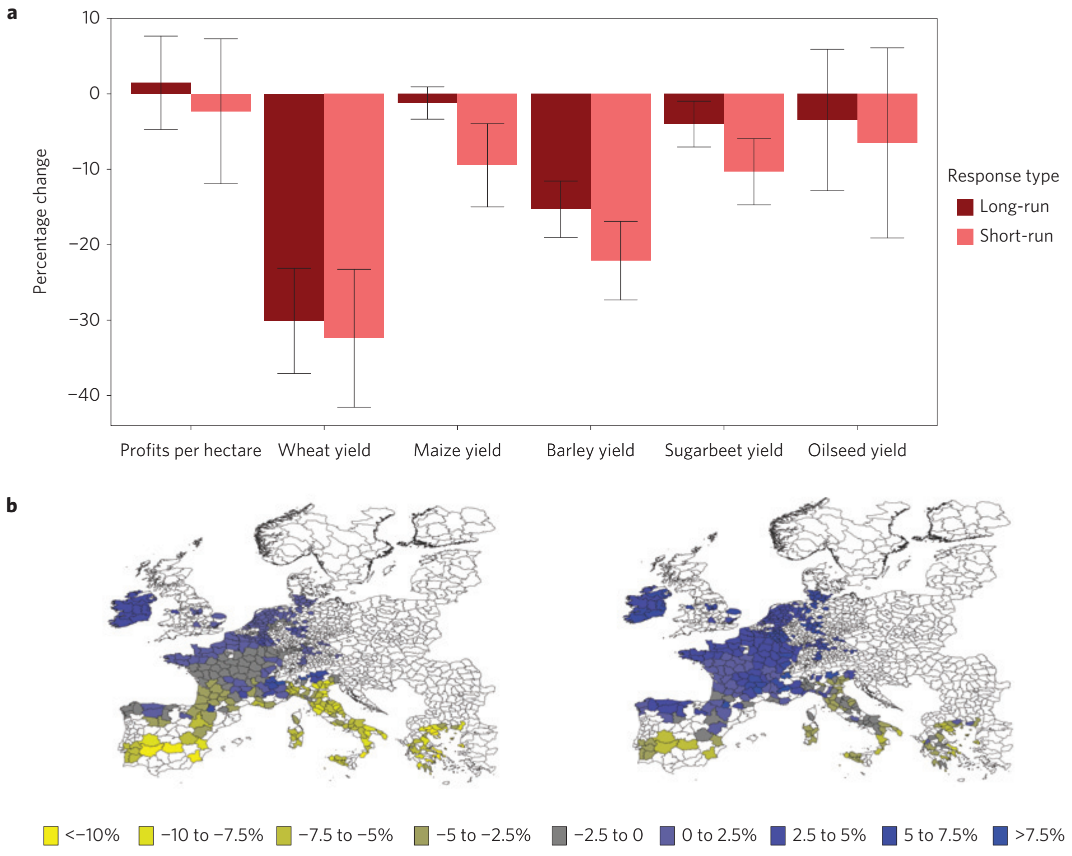

Figure 2 | Effects of warming on profits and yields. a, The impacts of temperature change by 2040 (2030–2049 mean) under the A1B scenario on farm profits and yields in Europe (production-weighted mean) relative to the 1961–1990 baseline. Dark colours show impacts including long-run adaptations; light colours show short-run impacts without adaptation. The difference between these can be interpreted as the potential for long-run adaptations to reduce the impacts of climate change. Error bars show the 95% confidence interval based on parameter (response) uncertainty (Methods). **b**, Maps of projected changes in farm profit by 2040 (2030–2049 mean) under the A1B scenario for growing regions included in the statistical model. The left map shows projections made using the short-run response function without adaptation and the right shows projections made using the long-run response function that includes private farm-level adaptation.

known response function and an uncertain autonomous adaptive response by farmers are, in most cases, a larger driver of projection uncertainty than variability in the climate forcing alone, at least as captured by the spread in climate model ensembles.

Our results contribute to a growing literature on the impacts of climate change on crop yields in Europe that uses both process-based models and statistical techniques. In agreement with several previous studies, we find that projected temperature changes are more important than precipitation changes in determining the impacts of climate change over the next few decades[9,10]. We find that the impact of mean temperature change on yield is around 5–10 times larger than the impact of precipitation by 2040. This is not because crop yields are insensitive to changes in precipitation, but because projected precipitation changes tend to be small whereas projected temperature changes are large relative to inter-annual variability. However, this analysis does not explicitly examine the effect of intra-seasonal precipitation variability or extreme events, which may be more significant than mean changes in impacting yields, particularly if variability increases under a warming climate[11].

Our statistical model implies that warming from climate change will have large negative impacts on wheat and barley yields throughout Europe, a finding consistent with previous work[12–14]. We project a large negative impact of future warming of 0.5% and 0.3% per year for wheat and barley yields, respectively. Our steep response functions for these crops and the fact that Europe has warmed substantially since 1980 are consistent with the observed levelling-off of these crop yields in the region, although other policy and economic factors may have also influenced this trend[12,13,15–17]. It should be noted that this projection does not include a number of moderating influences that may limit climate change impacts such as potential yield gains in southern Scandinavia or the CO_2 fertilization effect. CO_2 concentrations over this time period increase by approximately 50% in the A1B scenario, implying a fertilization effect of between 6% and 14% for C_3 crops[18,19].

We find negative but more moderate long-run impacts of warming on maize, sugarbeet and oilseed yield. Our very shallow long-run maize response curve is consistent with previous findings considering the growing season temperatures in our sample are consistently below 23 °C, a range where other studies have demonstrated relatively small temperature effects[5,9,20,21]. Moreover, maize grown in warmer parts of Europe is frequently irrigated, which may reduce sensitivity to extreme temperatures[22].

Relatively few studies have compared climate change impacts in Europe with and without adaptation and we believe none has done so empirically. The difference in projections made using the long-run and short-run response curves estimated here can be interpreted as the potential benefits of long-run adaptations. We find a fairly important role for adaptation in moderating the adverse impacts of warmer temperature on yields, although adaptation remains imperfect and there will be negative residual impacts of warming even if all adaptation options are adopted. The relative importance

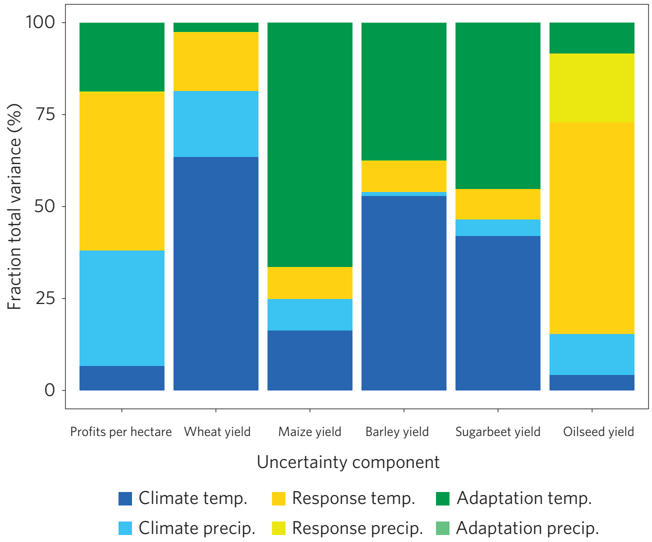

Figure 3 | Contribution of different factors to total uncertainty. Decomposition of the sources of uncertainty in projections of profits per hectare and yields under the A1B scenario for an ensemble of 13 model runs due to temperature change (dark colours) and precipitation change (light colours). Total uncertainty is scaled to 100 for each outcome to highlight the proportional contribution from each factor.

of adaptation differs between crops: adaptation has the potential to reduce adverse impacts on maize yields by 87% but the same fraction for wheat and barley yields are 7% and 31%, respectively. Although this analysis cannot identify the reasons for this difference, it could result from a number of factors including more extensive irrigation of maize or a wider range of cultivars in use across the study region.

Previous studies have compared either response and climate uncertainties[23] or present the spread of yield projections under different climate and adaptation scenarios[24,25]. However, the latter typically include only a limited number of possible adaptive responses (often changing planting date or crop variety) and therefore may underestimate the potential of the full suite of adaptation options available to farmers that are captured by our empirical approach[2]. We find that adaptation uncertainty is large for several crops (particularly maize, barley and sugarbeet), and the combination of adaptation and response uncertainty is, except for wheat yield, larger or comparable to uncertainty from climate model projections. Studies that attempt to quantify uncertainty using an ensemble of climate models but only a single adaptation scenario or yield response model may be significantly underestimating the true uncertainty in climate change impacts.

Methods

We use equation (1) to jointly estimate both the long-run effect of different climates and the short-run effect of annual deviations from this climate[6]. The economic model and relevant assumptions are described in the Supplementary Information. Equation (1) is used for each of six dependent variables: farm profits and the yields of five major crops. The farm profits/yields (V) for subnational region i, in country j in year t are estimated in the preferred model as:

$$\begin{aligned} V_{ijt} &= \beta_0 + \boldsymbol{\beta}_1 \bar{W}_{ijt} + \boldsymbol{\beta}_2 \bar{W}^2_{ijt} + \boldsymbol{\beta}_3 (W_{ijt} - \bar{W}_{ijt})^2 \\ &+ \beta_{4,j}\mathrm{Country}_j * \mathrm{Year}_t + \beta_{5,j}\mathrm{Country}_j * \mathrm{Year}_t^2 \\ &+ \beta_{6,j}\mathrm{Country}_j + \boldsymbol{\beta}_7 \mathrm{Controls}_{ijt} + \varepsilon_{ijt} \qquad (1) \end{aligned}$$

where $\bar{W}_{ijt}$ is a vector that includes growing season temperature and precipitation and is the 30-year climatological average for the years preceding year t. Bold denotes vectors of coefficients. We control for unobserved, possibly nonlinear time trends at the country level using a country-by-year linear and quadratic time trend, unobserved time-constant variation between countries using a country fixed effect, and other observed within-country variation using a suite of controls. These controls include a vector of soil-quality variables (organic carbon content, water-holding capacity, erodibility, and soil type), altitude and altitude squared, subsidies received per hectare, irrigated area per hectare and a crop-price index.

Our source of economic and yield data is the EU Farm Accountancy Data Network (FADN) survey between 1989 and 2009 (ref. 26). The data we use are aggregated from the farm to the regional (subnational) level using weights based on the three-way stratified sampling methodology used by FADN. Therefore, the representativeness of these aggregated values depends on the soundness of the sampling and weighting schemes used by the EU (ref. 26). Farm profits are defined as the total value of farm production minus all costs plus subsidies received minus taxes paid. They are normalized by the total agricultural area used in the year to give farm profits per hectare. Yields are calculated as the crop produced in the year divided by the area of crop planted. The five crops considered in this paper constitute around 25% of the value produced by European farms, with the remainder coming from meat and dairy production and other grain, fruit and vegetable crops. Weather data are monthly averages averaged over a growing season defined by the observed planting and harvest date for each region using the SAGE crop calendar data set[27–29]. For the profits per hectare regression we use a standard March–September growing season definition. We create balanced data sets by retaining only those observations with data for the whole period 1989–2009. This prevents possible confounding of the estimation by gradual entry of eastern European countries into the data set after the mid-1990s. Additional details on the construction of the data set and control variables are given in the Supplementary Information.

We estimate equation (1) using ordinary least-squares regression, weighting by the square root of farm area to reduce heteroskedasticity and to make results more representative of the average growing area. Standard errors were estimated using 500 block-bootstraps, blocking at the country by 2-year level to account for heteroskedasticity, within-country spatial autocorrelation, and temporal autocorrelation at one-year lag. The estimated response functions can be used to calculate the expected damages from climate change with (equation (2)) and without (equation (3)) adaptation. These responses are shown diagrammatically in Supplementary Fig. 1 and, given a shift in climate from $\bar{W}_0$ to $\bar{W}_1$ can be estimated for each observation as:

$$\Delta \hat{V}_{\mathrm{LR}i} = \hat{\beta}_1(\bar{W}_{1i} - \bar{W}_{0i}) + \hat{\beta}_2(\bar{W}^2_{1i} - \bar{W}^2_{0i}) \qquad (2)$$

$$\Delta \hat{V}_{\mathrm{SR}i} = \hat{\beta}_1(\bar{W}_{1i} - \bar{W}_{0i}) + \hat{\beta}_2(\bar{W}^2_{1i} - \bar{W}^2_{0i}) + \hat{\beta}_3(\bar{W}_{1i} - \bar{W}_{0i})^2 \qquad (3)$$

where the βs are the parameter estimates obtained from the equation (1) regression. These response curves are combined with climate model projections for the period 2030–2049 under the A1B scenario using a 13-member ensemble from the ENSEMBLES project[7]. The projections from this ensemble and the equations for decomposing ensemble projection uncertainty are described in the Supplementary Information. The ensemble we use pertains to a single emission scenario but scenario uncertainty constitutes only a small fraction of total uncertainty in climate projections at regional levels by 2040 and therefore is unlikely to affect our conclusions[30].

Received 7 October 2013; accepted 3 April 2014; published online 18 May 2014

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Acknowledgements
We would like to thank M. Burke for comments on the manuscript and the Stanford Interdisciplinary Graduate Fellowship for financial support for this project.

Author contributions
F.C.M. and D.B.L. designed the analysis. F.C.M. performed the analysis. F.C.M. and D.B.L. analysed results and wrote the paper.

Additional information
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Competing financial interests
The authors declare no competing financial interests.