Impacts of rising temperatures and farm management practices on global yields of 18 crops

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Abstract

Understanding the impact of changes in temperature and precipitation on crop yields is a vital step in developing policy and management options to feed the world. As most existing studies are limited to a few staple crops, we implemented global statistical models to examine the influence of weather and management practices on the yields of 18 crops, accounting for 70% of crop production by area and 65% by calorific intake. Focusing on the impact of temperature, we found considerable heterogeneity in the responses of yields across crops and countries. Irrigation was found to alleviate negative implications from temperature increases. Countries where increasing temperature cause the most negative impacts are typically the most food insecure, with the lowest calorific food supply and average crop yield. International action must be coordinated to raise yields in these countries through improvement and modernization of agricultural practices to counteract future adverse impacts of climate change.

Main

As part of the 17 UN Sustainable Development Goals (UN SDG), governments have agreed on a target to end hunger and ensure access to sufficient, nutritious food by 2030 for 850 million people. classified as undernourished globally[1]. Given the SDGs' interlinked nature[2], failure to reach this target risks undermining many others. Achieving food security represents a significant challenge, bearing in mind increases in global population, rising levels of affluence, a shift towards diets consumed in OECD countries, and climate change[3,4,5]. Indeed, the global food production system is particularly vulnerable to climate change, directly through the impact of temperature and precipitation[6,7], and indirectly through competition for land with negative emissions technologies and afforestation[8].

As the effect of climate change on crop yield is an established concern for global food security[9], the impact of historical variation in weather has provided valuable insights[7,10,11,12] with both process-based and statistical models reaching similar conclusions about the impact of future climate[9,13,14.] Since the current literature has so far focused on a few staple crops, there is an identified need to broaden our understanding across a wider range of crop types[15].

By implementing statistical modelling, we assess the impact of weather variation on crop yield for 18 crops. Specifically, empirical literature has primarily focused on the impact of weather on six major crops specifically wheat, maize and soybeans[10,11,16], rice[10,16], barley[11,12,17] and sugar beet[12,17]. Our analysis also includes cassava, cotton, groundnuts, millet, oats, potatoes, pulses, rapeseed, rye, sorghum, sunflower and sweet potatoes. Together, these crops represent 70% of the global crop area[18] and around 65% of global calorific intake. Besides modelling a wider set of crops, we extend previous approaches[10] by accounting for additional factors affecting crop yield – including pesticides, fertilisers and irrigation – to provide insights into the role of agronomy in ameliorating the impacts of changing climate. We focus our discussion on the effect of temperature given that the empirical relationship of crop yield with temperature is much better understood than with other weather factors[19] (and, in some cases, temperature was found to be the predominant factor in explaining crop yield variability[20].

Results

Marginal impact and optimal growing conditions

We estimated an inverted U-shaped relationship between temperature and crop yields for all 18 crops, with the values for the optimal temperature reflecting credible conditions of crop production (Supplementary Table 1). Statistically significant estimates for precipitation are harder to achieve, also reflecting previous results[21]. In 10 of the 18 crops assessed in this study, an increase of 10 mm in precipitation induces a decrease in the yields, evaluated at the global mean, while in the remaining crops the impact is positive. Analysis of the impact of a 1°C rise in temperature on the set of 12 crops rarely assessed in the literature highlights a negative impact across the majority of countries growing cassava, cotton, groundnuts, millet, oats, pulses and rye, and a positive impact for those crops with the highest levels of global consumption (i.e. potatoes, sweet potatoes, rapeseed and sorghum). From a food security perspective, three crops widely consumed in developing countries tend to be either positively affected (sorghum and sweet potatoes) or suffer a small reduction in the yield (cassava) in response to a 1°C increase. By definition, the marginal effect described assumes no changes in other factors, when in reality changes in temperature are likely to occur in the presence of changes in other factors, such as precipitation. In some case, the changes in temperature considered here could imply lack of analogue historical climatic conditions.[22] Such 'novel climates' greatly increase the uncertainty of the estimated impacts of our models, as extrapolation occurs outside of the sample used in the estimation.

Our results support the role of adaptation in global agriculture, as we demonstrate that agricultural management practices such as irrigation can ameliorate the negative impacts on crop productivity. Pesticides and fertilisers are generally found to enhance crop productivity. The use of pesticides has a positive impact on the yield of about half of the crops in our sample, specifically potatoes, pulses, rice, sugar beet, sunflower, sweet potatoes and wheat. Fertiliser use contributes to increasing yields of sugar beet, sunflower and sweet potatoes. The impact of pesticides and fertiliser is modelled through a linear approximation without allowing for interaction with other factor such as temperature.

Figure 1 illustrates the functional relationship between crop yield and temperature in countries with low irrigation (black curve) and high irrigation (red curve), using cassava as an example. The curves are obtained by assigning the value zero to all the non-temperature variables in Supplementary Table 1 (except irrigation), since using a different value for those variables would affect the level of the yield but not the shape of the yield-temperature relationship. In Figure 1, the gently sloping curves indicate a relatively small variation in the marginal effect of temperature as the level of temperature changes, i.e. the first derivative of the red and black curves. In fact, for cassava, the impact of a 1°C increase in temperature across the globe varies between -3% and 1% in both low and high irrigated countries.

Irrigation allows for a higher optimal temperature, i.e. the vertex of the parabolas in the figure. These are ca. 26°C in countries with high levels of irrigation compared to ca. 20.5°C in the remaining countries.

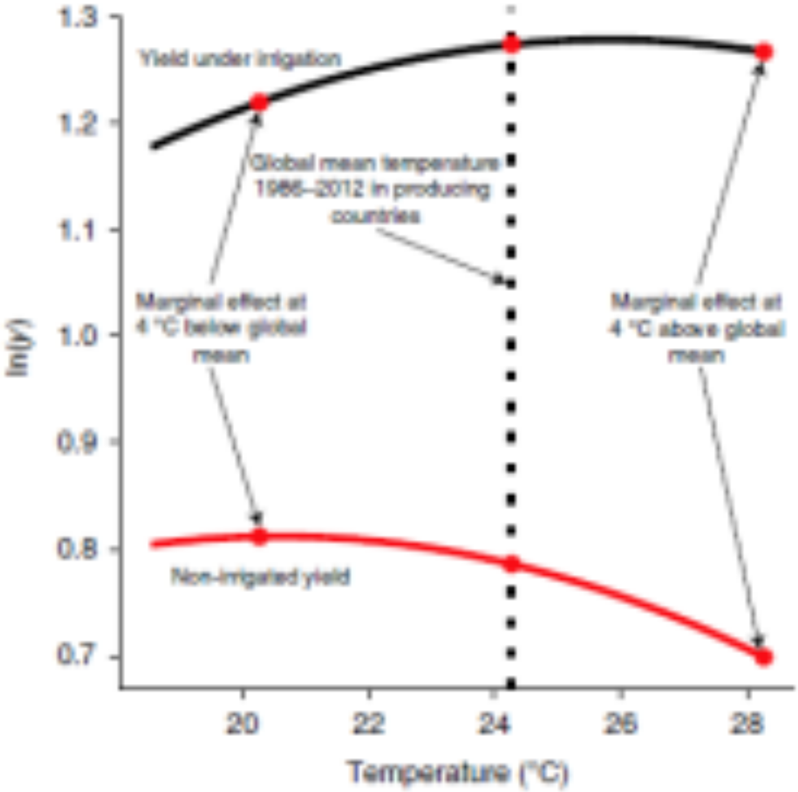


Figure 1. **Functional relationship between temperature and crop yield of cassava.** The red dots indicate the global mean (middle point) and the points which are 4°C colder and warmer than the global mean. The marginal effect of temperature increasing 1°C is indicated at these three points in column A of Figure 2. The functional relationship is indicated by the red curve when irrigation is low, and the black curve when irrigation is high.

Estimated optimal temperatures tend to occur near the global mean for a number of crops (see column A of Figure 2). This implies that warming temperatures will deliver yield increases, at least initially, in some of the growing countries. The number of countries benefiting from temperature rises however decreases with the magnitude of the rise, as more and more countries are pushed beyond the optimal level of temperature. More detailed results from the statistical crop yield models can be found in Supplementary Table 1.

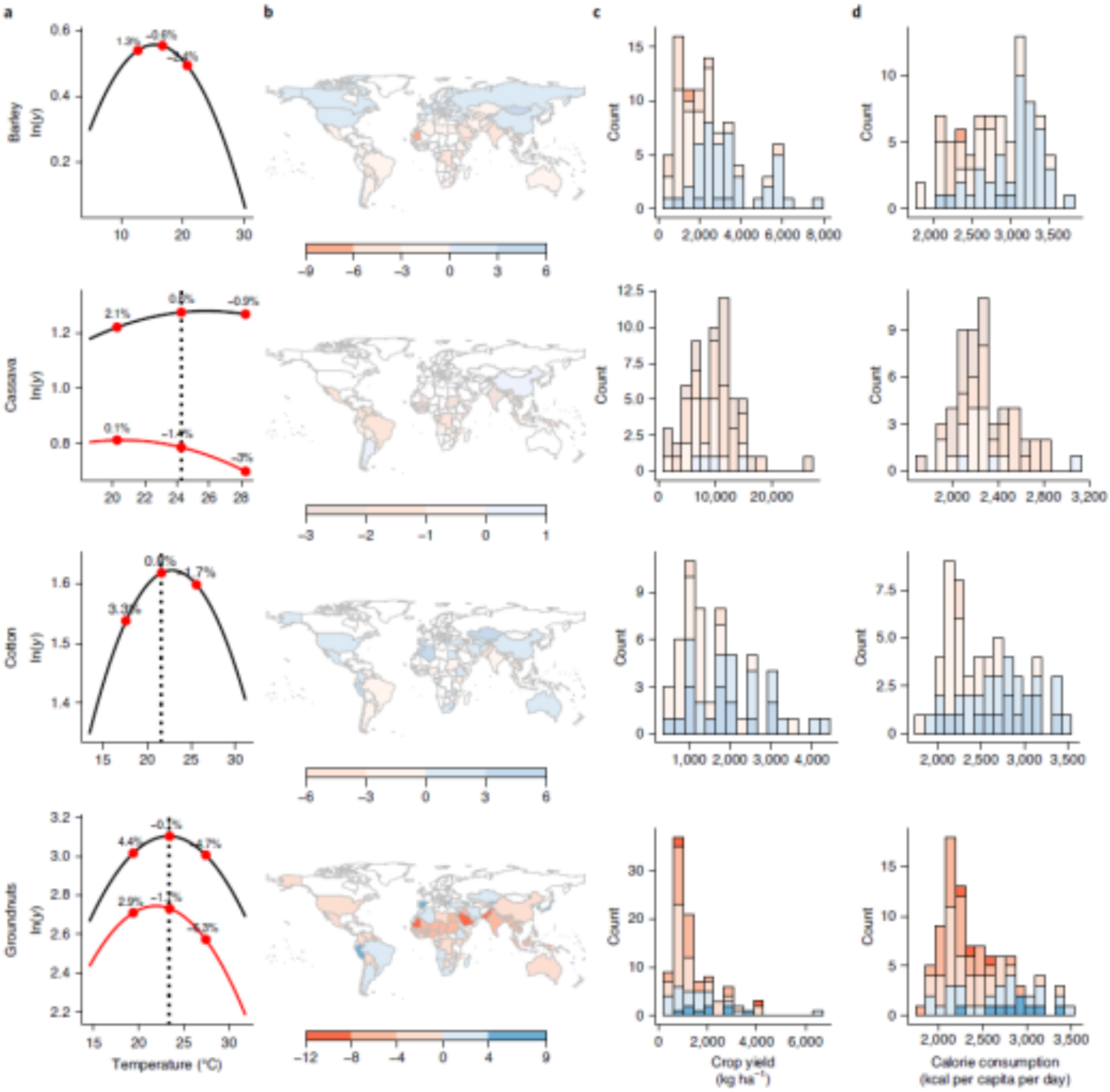


Fig. 2 | Impacts of rising temperatures on crop yield and food safety globally for barley, cassava, cotton and groundnuts. a, The functional relationship between temperature and crop yield. The global temperature mean computed over 1986–2012 in the countries cultivating a specific crop is indicated by the central dot and vertical dashed line. The other two dots indicate temperatures 4 °C warmer and 4 °C colder than the global mean. The percentage next to the dots indicates the marginal effect, as explained in Fig. 1. **b**, The geographical distribution of the marginal effect related to a 1 °C temperature rise. The colours indicate the percentage change in the crop yield for a country expected as a consequence of an increase of 1 °C. The range of the colour scale reflects the marginal sensitivity to temperature estimated in our study. **c**, The frequency distribution of crop yield (kilograms per hectare) by country with the marginal effect of a 1 °C temperature increase. For each point in the bars of the histogram, the colours indicate the value of the marginal effect according to the colour scale in **b**. **d**, The frequency distribution of crop yield (kilograms per hectare) by average calorie intake (kilocalories per capita per day), using the same colour scheme as the one described for the histograms in **c**.

Figure 2.

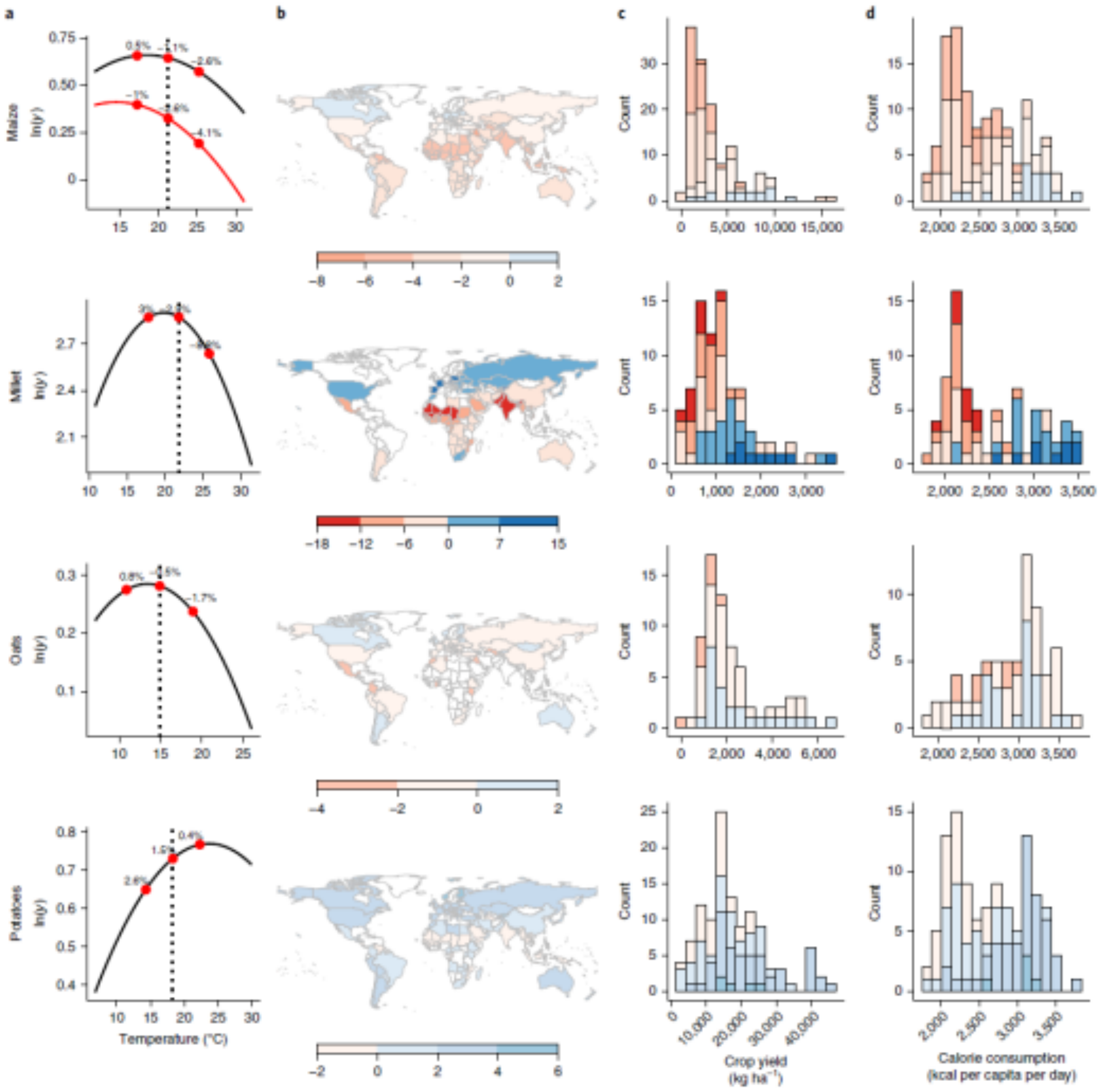


Fig. 3 | Impacts of rising temperatures on crop yields and food safety globally for maize, millet, oats and potatoes. More details can be found in the caption of Fig. 2.

Figure 3. Impacts of rising temperatures on crop yields and food safety globally for maize, millet, oats, potatoes. More details can be found in the caption of Figure 2.

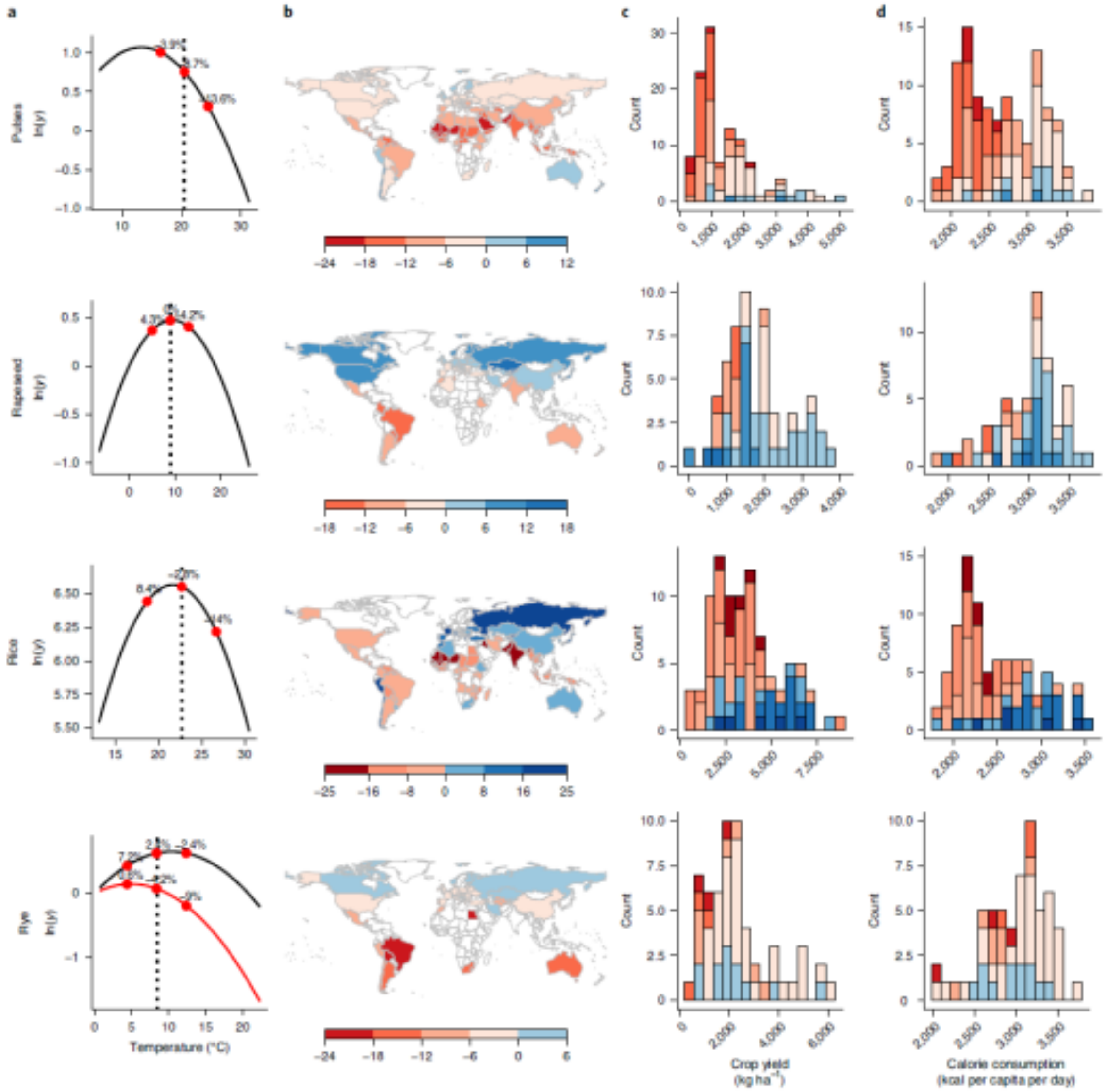


Fig. 4 | Impacts of rising temperatures on crop yields and food safety globally for pulses, rapeseed, rice and rye. More details can be found in the caption of Fig. 2.

Figure 4. Impacts of rising temperatures on crop yields and food safety globally for pulses, rapeseed, rice and rye. More details can be found in the caption of Figure 2.

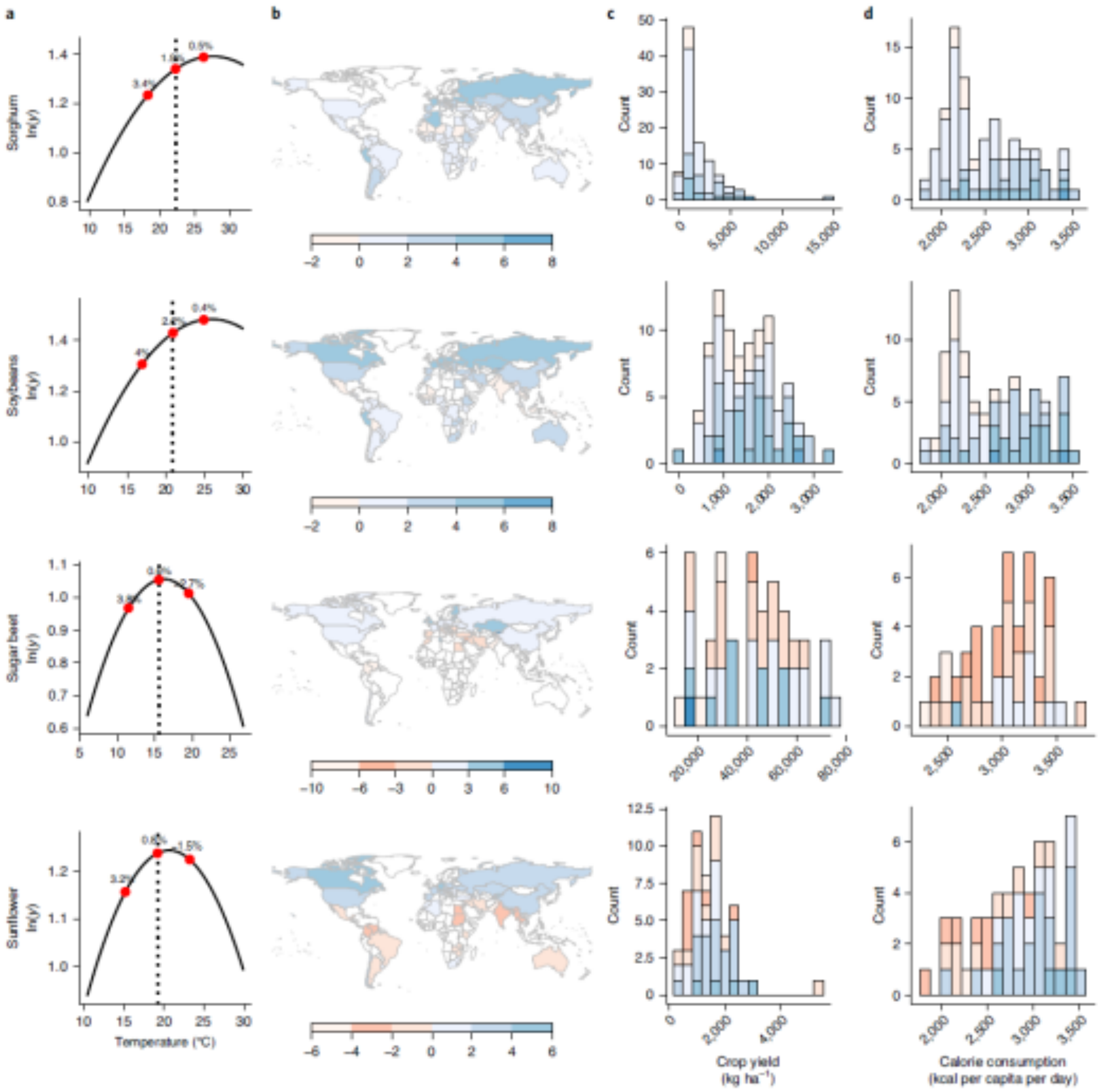


Fig. 5 | Impacts of rising temperatures on crop yields and food safety globally for sorghum, soybeans, sugar beet and sunflowers. More details can be found in the caption of Fig. 2.

Figure 5. Impacts of rising temperatures on crop yields and food safety globally for sorghum, soybeans, sugar beet and sunflower. More details can be found in the caption of Figure 2.

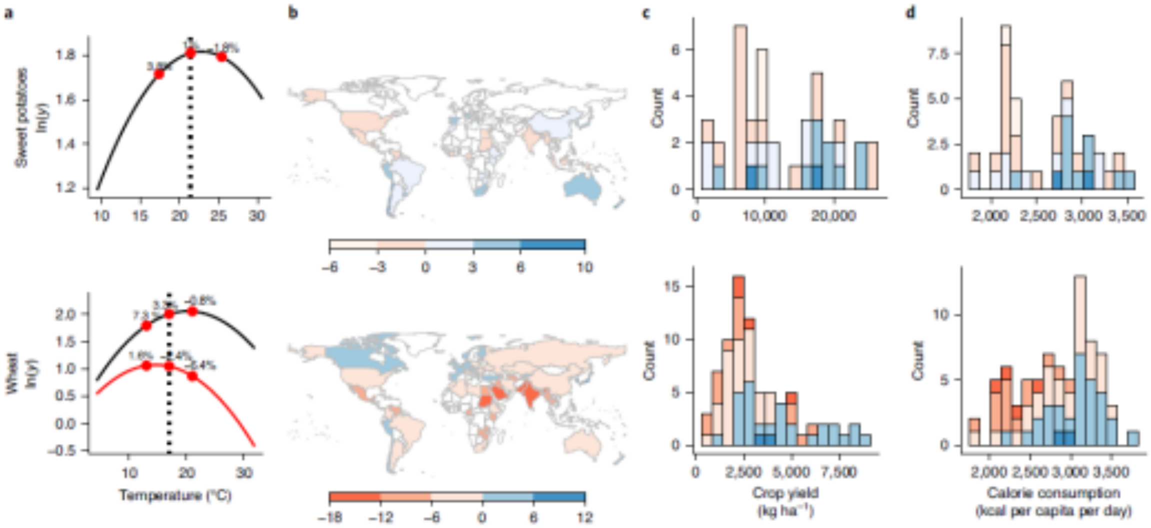


Fig. 6 | Impacts of rising temperatures on crop yields and food safety globally for sweet potatoes and wheat. More details can be found in the caption of Fig. 2.

Figure 6. Impacts of rising temperatures on crop yields and food safety globally for sweet potatoes and wheat. More details can be found in the caption of Figure 2.

Heterogeneous marginal impact of temperature across the globe

Major crops tend to be negatively affected by a 1°C increase, as a 2.8%, 2.6% and 2.4% decrease in the yield is estimated for rice, maize and wheat, when evaluated at the global mean temperature of each crop. This contrasts with yields of potatoes and soybeans that increase by 1.5% and 2.2% respectively. Comparison of marginal effect at the global mean is reductive as the effect of temperature varies across countries. Winners and losers from raising temperatures can be identified by evaluating the marginal effect of 1°C increase from the mean observed in each country over the 1986-2012 sample (see

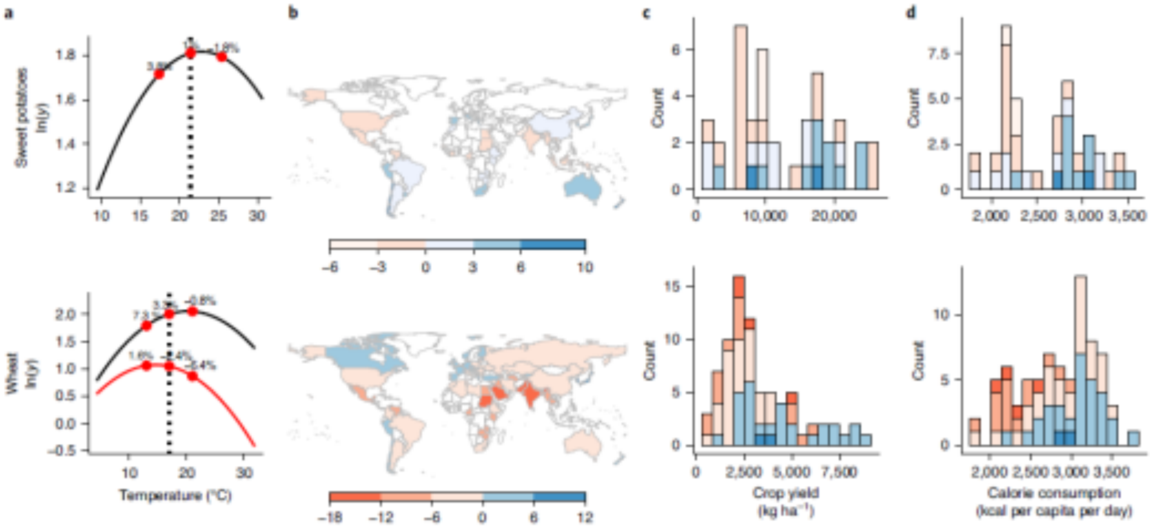


Fig. 6 | Impacts of rising temperatures on crop yields and food safety globally for sweet potatoes and wheat. More details can be found in the caption of Fig. 2.

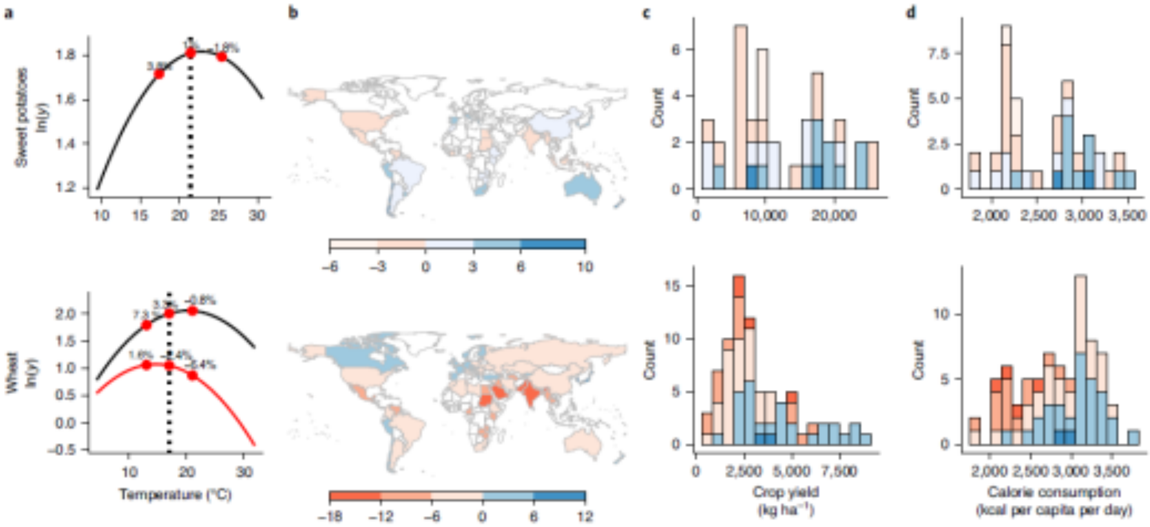


Fig. 6 | Impacts of rising temperatures on crop yields and food safety globally for sweet potatoes and wheat. More details can be found in the caption of Fig. 2.

Methods). The maps in column B of Figure 2-Figure **6**. clarify that most countries are negatively (red countries) instead of positively affected (blue countries). Maize, oats, pulses and wheat are widely impacted by rising temperatures, as yield decreases in almost all countries while potatoes, sorghum, soybeans and sugar beet overall benefit from rising temperatures. The plots in column B of Figure 2-Figure **6** show the sensitivity of different crops to increases in the temperature. Ranges as wide as 30 percentage point can be observed in the case of millet, pulses, rapeseed, rice and rye. Conversely, cassava, oats and potatoes are among the crops least affected by a 1°C increase, with the range of marginal impact being under 10% percentage points in all cases (see Figure 3-Figure 4). However, crops with a highly diverse marginal impact of temperature tend have a much smaller range for the great majority of countries where they are grown. As an example, the range of the

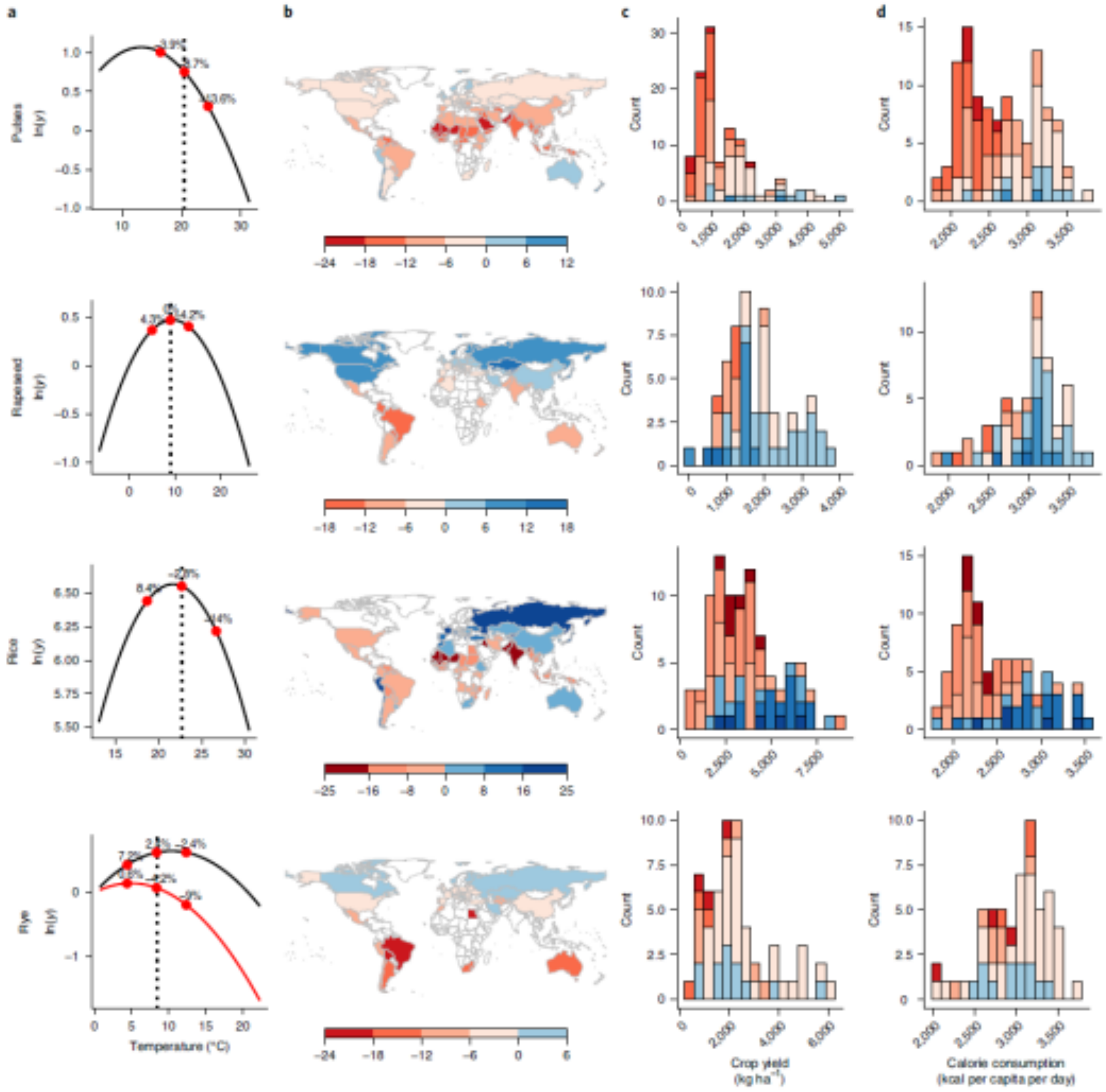


Fig. 4 | Impacts of rising temperatures on crop yields and food safety globally for pulses, rapeseed, rice and rye. More details can be found in the caption of Fig. 2.

marginal impact in 80% of the countries where rice is grown is only half the width shown in

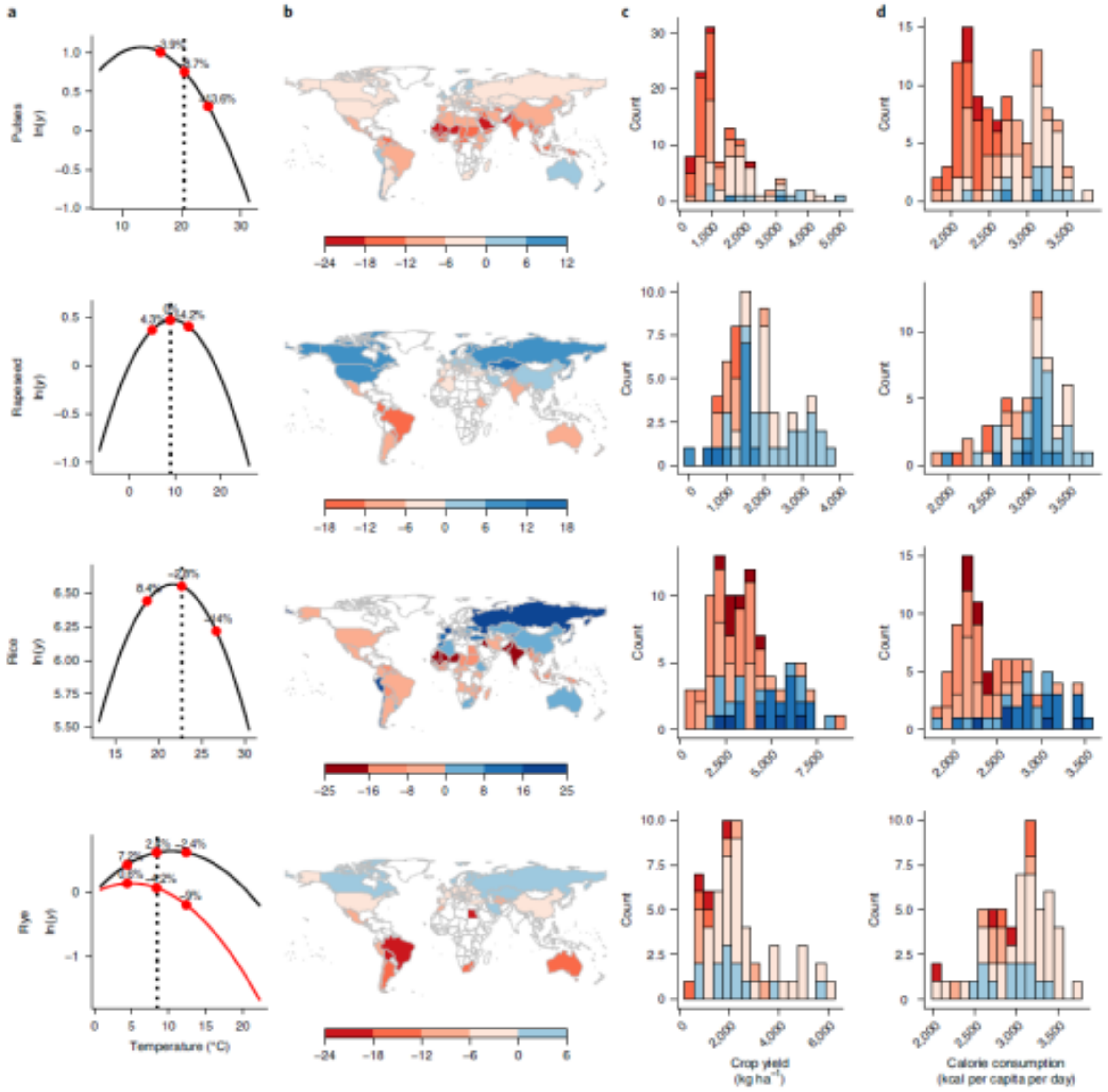


Fig. 4 | Impacts of rising temperatures on crop yields and food safety globally for pulses, rapeseed, rice and rye. More details can be found in the caption of Fig. 2.

Figure **4**.

Impact on food security and productivity

The wide productivity differences across countries will be exacerbated by rising temperatures, unless corrective action is taken. We explore this by assessing the relationship between prevailing yield and the marginal effect of temperature, as shown in column C of Figure 2- Figure **6**. The highest positive marginal effects are scattered throughout the geographical distribution of crop yield, while the most negative impacts tend to be in countries, such as those in sub-Saharan Africa, that have not benefited from the Green Revolution[23]. This is particularly strong in the case of barley, maize, millet, pulses, rice and wheat. A similar pattern can be observed in the case of the relationship between the daily intake of calories and the marginal impact of temperature – see column D of Figure 2-

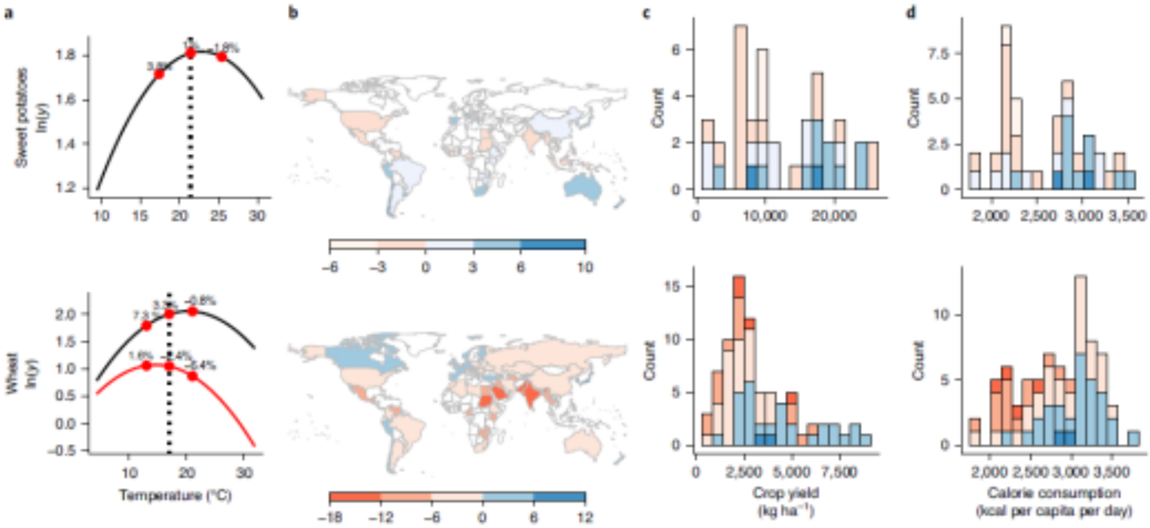


Fig. 6 | Impacts of rising temperatures on crop yields and food safety globally for sweet potatoes and wheat. More details can be found in the caption of Fig. 2.

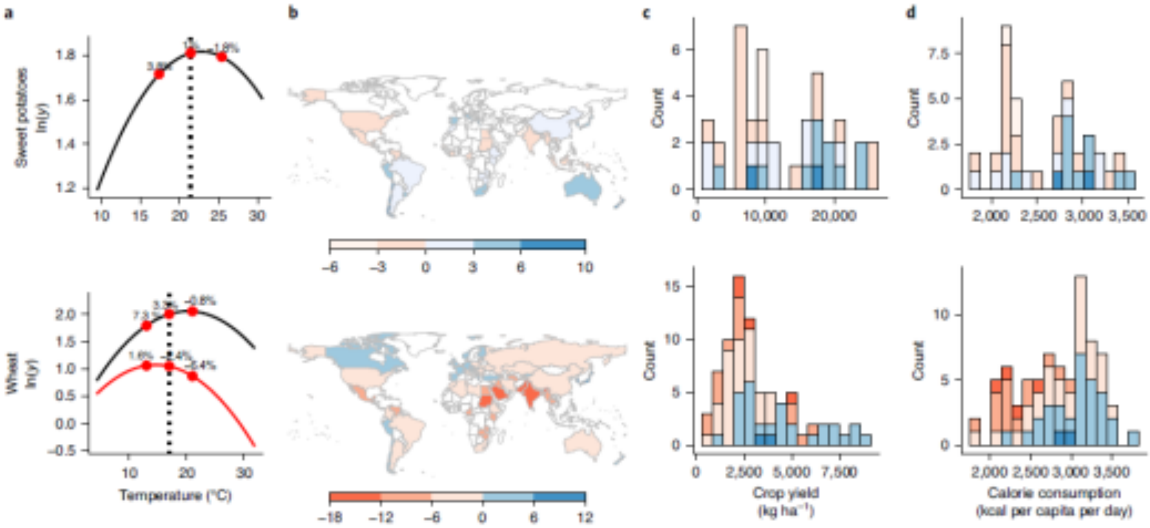


Fig. 6 | Impacts of rising temperatures on crop yields and food safety globally for sweet potatoes and wheat. More details can be found in the caption of Fig. 2.

Figure **6**, as most of the countries which are worst affected by warming temperatures have very low daily calorific intake. This is a concerning finding, as the countries with the worst level of food security (as measured by the daily intake of calories) are also worst affected by rising temperature.

Discussion

Crop dependence on temperature and agronomic practice

Weather variables significantly contribute to the yield variability of the 18 crops studied here. Our analysis confirms results from existing global studies focusing on maize, rice, soybeans and wheat[21,10] and shows at global scale that potato, the most widely produced non-grain crop in the world, as well as sorghum and soybeans are resilient to moderate increases in temperature – thus confirming previous results in the case of soybeans[24].

In five of the modelled crops, irrigation implies higher optimal temperatures and more positive impact of rising temperatures. This confirms, at global scale, the results from previous studies focused on the USA[11,25,26]. Irrigation has been argued to limit evapotranspiration demand related to heat[10] and have cooling effects on the canopy temperature reducing the impact of heat and drought stress on crop yield.[27] Similarly, the role of irrigation intervals in maximising the functioning of the stomata and enhancing photosynthetic and yield efficiency has been examined in the literature.[28] Some producers facing negative impacts of temperature, e.g. Israel and Greece, have invested in irrigation (the effects of rising temperatures would have been worse without such schemes). Expansion of irrigation may be possible in some cases, but in many countries, notably in Africa, expansion of land under irrigation is impractical or impossible.[29] Alternative options for the management of rainfall (e.g. through collection and soil management) exist and should be integrated into agricultural policy where appropriate.[29]

Countries with very low yields use a low amount of pesticides and fertilisers, while highly productive countries tend to have a higher-than-average consumption of pesticides and fertilisers. For example, wheat yields in the 10 countries with the highest level of pesticides (4,177 kg/ha) were more than double the level observed in the 10 countries with the lowest consumption (1,857 kg/ha). As pesticides and fertilisers have a strong effect on a number of crops, some of the yield difference across countries could be overcome by increasing their use, although this may be associated with other environmental challenges. We observe that high use of fertilisers and pesticides may serve to even out the effect of management intensity across countries and so compensate for decreases in the yield brought about by rising temperatures. Although not explored in this study, the interaction between marginal impacts of temperature and the use of fertilisers and pesticides should be urgently addressed by empirical studies. As an example, evidence of the marginal effect of temperature being lower in African countries with low use of fertilisers has been discussed before.[30] Similarly, as rising temperatures facilitate the diffusion of pests[31], marginal impact of weather can be influenced by the level of pesticides. In both cases, future research should explore the suitability of non-linear functions – rather than adopting the linear approximation discussed here – to consider for example decreasing marginal gains from the application of chemical inputs, or their interactions with other factors such as temperature. The level of pesticides and fertilisers could in principle be a proxy for other aspects of management such as mechanisation or advanced cultivars, but only if there is correlation between these factors and fertilisers or pesticides in a significant number of countries.

Additional adaptation options

The wide range of marginal impacts from temperature increases seen across the 18 crops suggests that substituting highly sensitive crops by those more resilient to temperature increase is a potential adaptation strategy to rising temperatures. While likely to take place across countries, this substitution may severely impact the diversity of crops used in agriculture. This is an aspect which should be assessed as a matter of urgency by empirical studies. Development of crop varieties matched to not only current conditions but also those likely to develop in the coming decades is an area of substantial current research interest.[32] Notably in Africa, where many countries worst affected by rising temperatures are located, the Green Revolution has been harder to establish due to a broad range of environmental and socio-economic factors[23]. Maize yields in the USA were found to be less sensitive to extreme heat days in hotter climates[33], demonstrating that the response to temperature can be substantially reduced by the choice of cultivars. On the other hand, a trade-off between yield levels and the robustness to heat has also been found among new varieties[34]. Typically associated with higher environmental and/or economic costs, increased use of agricultural chemicals and expansion of cropping area are obvious routes to address food insecurity, which could decrease reliance on imports. From an environmental sustainability perspective, these routes are obviously problematic and could be counterproductive for meeting the SDGs agenda.

With regard to changing growing season, early planting dates failed to increase the US yield of maize, millet and wheat[35], but higher yields of US maize could be obtained if high planting rates are combined with delayed planting dates[36]. This seems an area where further research is also urgently required, especially taking into consideration the impact of changing a crop's planting and harvest dates on the crops which are planted subsequently. Crop switching is another factor potentially reducing the impact of rising temperatures on crop yield.[37] Negative welfare impact arising from the climate scenarios for Africa in 2100 could fully be counteracted by switching crops[38]. Qualitative studies focusing on specific locations however point out obstacles to crop switching, primarily influenced by economic, political, and social rather than climate factors[39]. Benefits arising from crop switching can be highly crop-dependent even when assessed for the same location[40].

Another factor which might help counteract the negative impact of rising temperatures is CO_2 fertilisation. C3 crops, i.e. rice, wheat, soybeans, rye, barley, cassava and potatoes, are more sensitive to CO_2 compared to C4 crops, i.e. maize, sorghum and sugarcane, with low sensitivity in the latter due to CO_2 being already saturated, although increases in transpiration efficiency might occur under dry conditions[41]. Crop response to elevated CO_2 remains the largest source of uncertainty in crop yield studies[42], but expected gains have been revised downwards by Free-Air Concentration Enrichment (FACE) studies which are more representative of field growing conditions than earlier chamber studies[43] The impact of CO_2 fertilisation was found to reduce or disappear under wetter, drier and/or hotter conditions when the forcing variable exceeded its intermediate regime[44]. In addition, increasing CO_2 is expected to negatively affect the quality of grains by reducing the overall protein content[45] and may require large quantities of fertilisers[41]. Incorporating the effects of CO_2 in empirical modelling is challenging, as CO_2 does not have any spatial variation and changes only slowly across time. A number of potential avenues have been discussed previously[9]. Introduction of CO_2 fertilisation in process-based model is more straightforward, but without greater clarity on the impact of CO_2 from FACE studies, coefficients used in process-based model are likely to be highly unreliable.

Implications for food security and productivity

Our results investigate the relationship between the impact of rising temperatures and the existing level of crop yields for a large set of crops and over a wide temperature range. In fact, we look explicitly at the existing level of crop yield rather using proxies such as latitude and GDP[42,46]. There are a number of institutional routes to address the impacts of warming temperatures on food security and productivity, although substantial costs and barriers may be associated with them. These include increasing technology transfer to the worst affected countries and sharing targeted agronomic research advances. International donors might facilitate these processes and coordinated action to raise yields through improved agronomic practices and modernization of the agronomic system, while managing potentially negative effects of farming intensification[47]. This is particularly important in countries with prevailing low productivity and inadequate diets[48].

Changing harvesting area is also an important consideration for food security and productivity. Our research flags the countries which are likely to stop production of a certain crop, that is, those with high marginal negative impact and low productivity. New marginal producers, i.e. countries with climatic condition similar to those with the highest positive marginal impact[49], are also likely to emerge. Finally, the role of international trade in this context should also be explored, bearing in mind that rising temperatures are likely to impact international trading patterns as the absolute advantage to trade is projected to change across countries.

Methods

Overview

The models described below explore the sensitivity of crop yield to a number of factors, including weather, but also irrigation and management practices such as the use of pesticides and fertilisers, by making use of a dataset that spans the 1986-2012 period. The analysis is implemented for 18 crops: barley, cassava, cotton, groundnuts, maize, millet, oats, potatoes, pulses, rapeseed, rice, rye, sorghum, soybeans, sugarbeet, sunflower, sweet potatoes and wheat. This set of crops uses all the data (with the exception of yams) available in a commonly used gridded crop calendar[50], which is required to compute weather variables as described below. The specification search, which follows the General-to-Specific framework[51] in terms of modelling approach and the variables used in the model, incorporates considerations related to statistical significance, and therefore the precision of the estimates, as well as the sign of the estimated marginal impacts from agronomic literature and previous studies. Our analysis covers at most the years between 1986 and 2012, although the specific start and end years vary across countries and modelled crops, as a result of shorter available time span for some of the variables (see below). The time period used in this study is comparable to that of previous contributions[10,11,12,17,21] and is considered adequate to analyse the implications of weather factors for crop yields. Countries covered in the dataset vary across crops, reflecting requirements in terms of growing conditions and dietary habits.

Data

Crop yield is defined as the harvested production per unit of harvested area with data collected from the online dataset of the Food and Agriculture Organization of the United Nations (FAO), i.e. FAOSTAT Database Agricultural Production. These are annual time series at country level. Weather variables are included in terms of their monthly average weighted across the growing season. Data for irrigation, pesticides and fertilisers are available only for total agricultural activity, e.g. tons of fertilisers used in the agricultural sector as a whole, rather than in the cultivation of a specific crop. In addition, fertiliser data are available for a limited number of countries compared to the set of countries for which crop yield data are available. These are limitations of the available datasets which influence the way in which specification search is implemented, as discussed below.

- Information for **pesticides**, defined as the average use per area of cropland (kg/ha), is taken from FAOSTAT Database Inputs. Annual data are available at the earliest from 1990 onwards for 164 countries, although the actual start year of the dataset varies across countries;
- Data for **irrigation** (area irrigated in hectares) are obtained from the Global Map of Irrigation Areas (GMIA) used by FAO's Information System on Water and Agriculture (AQUASTAT). This dataset is available for the year 2005 for 196 countries. We computed irrigated agricultural areas as a percentage of agricultural areas by using agricultural area retrieved from FAOSTAT Database Inputs and we then divided countries into two groups, those with intensive irrigation systems, i.e. countries with more than 10% of their agricultural area being irrigated (a group of 39 countries) and those not characterized by an intensive irrigation systems, i.e. countries with less than 10% of their agricultural area being irrigated (resulting in a set of 157 countries);
- Data for **fertilisers**, taken from IFASTAT of the International Fertilisers Association (IFA), are expressed as consumption (in metric tons) of Grand Total Nitrogen in 2005 for 109 countries. By using cropland information from FAOSTAT Database Inputs, we express consumption of fertilisers per hectare of cropland, so as to obtain data comparable to those available for pesticides;
- The **weather** variables include country-level temperature (measured in °C) and precipitation (measured in millimetres). We follow established practice in the literature[10,16] to construct weather variables by averaging monthly weather observations based on a constant crop growing season[50] and areas where the crop is cultivated[18]. Thus, only weather fluctuations specific to the production of each crop are considered, leading to a precise identification of the impact of temperature and precipitation on yield. This implies combining three different datasets:
    1) monthly average of temperature and precipitation on a grid of 30min resolution, collected from the Climate Research Unit of the University of East Anglia[52];

2) a map of cropland at 5min resolution[18]; and
3) a crop calendar, which provides the growing season for each crop on 5min resolution[50].

The weather variables correspond to daily (or diurnal) average temperature and total precipitation, by combining monthly anomalies and monthly climatology[52]. All crops have one growing season in the crop calendar[50], apart from maize, rice and wheat - which have main and secondary season and for which we used the main season (similarly to [10]). The possibility of multiple cropping on the same land plot should not have an impact on the outcome of this analysis, as the focus is the crop yield and not land requirements for cropping.

Our analysis uses country-level datasets due to the obvious difficulty of accessing global datasets at the sub-country level. The need to use datasets covering multiple countries also influenced our choice of weather variables. As historical hourly weather data are challenging to aggregate across a variety of growing regions[26], our study follows the established practice of using monthly averages of temperature and precipitation in linear and quadratic terms[10,12,21]. Such specifications align with the agronomic literature with regard to crops best growing within a range of temperature and precipitation, beyond which weather factors become harmful for production. We pool together all countries growing a specific crop, as previous analyses with specific country groups[10] have shown that the estimated impact of temperature and precipitation is comparable across groupings.

The choice of the time span for this study (1986 to 2012) mirrors other studies in the literature[10]. However, for the models including pesticides, the start year of the sample in this study is 1990 due to data availability. Our analysis covers at most the timespan from 1986 to 2012 to maintain comparability with existing studies[11,17,21,53] and across models estimated in this article. We followed the majority of contributions in the literature by adopting panel approaches to benefit from a much higher number of observations, a dataset incorporating more variation compared to a single time series, and the ability to control for omitted variables- especially if their variation across time is limited. On the one hand, estimation is also more straightforward as, from a statistical perspective, there is no need to deal with stochastic or deterministic trends as one would when dealing with a single times series. On the other hand, given the global coverage of our dataset and the possibility of large differences in cultivars and agronomic practice between countries, optimal growing condition could vary considerably. Evidence against this possibility has been explored in a dataset similar to the one used in this study[10]. Subgrouping of countries in the panel was not found to be very influential on the results of their analysis. In addition, optimal temperature in the case of sugar beet estimated here are very similar to those we obtained using a time series approach for single European countries, as part of the follow-up study to [6]. It is important to mention that a different optimal temperature does not imply necessarily a change in the value of the marginal effect which is the key metrics in this study, as the marginal effect or a specific country is determined not only by the optimal temperature but also by the curvature of the parabola being estimated.

Statistical models

This study makes use of a comprehensive collection of panel data models, with the subscripts i and t indicating country and year, respectively. The most general model includes a country-specific quadratic trend (t, t^2), an individual specific time-invariant component, α_i, a common time-variant component, λ_t, as well as a set of observed variables potentially affecting crop yield, included in the vector $\mathbf{X}_{it}$. This specification, in which y_{it} represents the logarithm of crop yield and ε_{it} a random disturbance, reads as follows:

$$y_{it} = \alpha_i + \lambda_t + \rho_{1i}t + \rho_{2i}t^2 + \boldsymbol{\beta}\mathbf{X}_{it} + \varepsilon_{it} \tag{1}$$

In the second-most general model, the common time-variant component, λ_t is dropped so that:

$$y_{it} = \alpha_i + \rho_{1i}t + \rho_{2i}t^2 + \boldsymbol{\beta}\mathbf{X}_{it} + \varepsilon_{it} \tag{2}$$

while by dropping the country-specific quadratic trend and reinserting the common time-variant component, λ_t, one obtains:

$$y_{it} = \alpha_i + \lambda_t + \boldsymbol{\beta}\mathbf{X}_{it} + \varepsilon_{it} \tag{3}$$

It is worth noting that coefficients of the quadratic time trends are allowed to differ across countries, while the coefficients of all other components are assumed to be constant across countries[10]. By including country specific time trends, we aim to account for factors like technological advance or other time-varying features that could possibly influence crop productivities. We capture country-based unobserved effects by estimating models using either fixed effects or random effects; the choice between the two is based on the Hausman test. In the case of soybeans, omitted variable bias is absorbed by estimating the model in first differences. A global trend is included in this case, instead of a country-specific trend driven by the model's fit which has been more challenging comparing to all other crops of our sample. We also estimated models pooling the dataset and providing estimates based on country-specific averages across time (individual between estimator) or time-specific averages across countries (time effects between estimator).

Set of Explanatory Variables

In our analysis of the impact of weather factors and management practices on crop yield, the most general set of control variables, $\mathbf{X}_{it}^{\mathbf{1}}$ includes:

1) temperature and precipitation incorporated in both their levels and their squared terms[10];
2) an indicator of the extent to which irrigation is deployed in the whole agricultural sector, with the indicator taking a value equal to one for countries with more than 10% of their agricultural area being irrigated and a value equal to zero otherwise. This indicator is interacted with the linear terms of the weather variables, so that temperature and precipitation are allowed to have a different optimal value in countries making extensive use of irrigation;
3) use of pesticides and fertilizers in the whole agricultural sector.

$$\boldsymbol{\beta}\mathbf{X}_{it}^{\mathbf{1}} = \big[\beta_1 Temp_{it}^2 + \beta_2 Temp_{it} \cdot Irr_i + \beta_3 Temp_{it} + \beta_4 Prec_{it}^2 + \beta_5 Prec_{it} \cdot Irr_i + \beta_6 Prec_{it} + \beta_7 Pest_{it} + \beta_8 Fert_{it}\big] \qquad (4)$$

When the full vector of controls was not used, our attention was primarily focused on the interaction between irrigation and temperature, following recent studies exploring such a relationship[11]. For this reason, we chose to start dropping the factors related to management practice, i.e. $Pest_{it}$ and $Fert_{it}$, and only if no viable models are delivered by the search specification below, we drop the interaction term between irrigation and weather factors, i.e. $Temp_{it} \cdot Irr_i$ and $Prec_{it} \cdot Irr_i$ so that the set of variables included in the models are respectively:

$$\boldsymbol{\beta}\mathbf{X}_{it}^{2} = \left[\beta_1 Temp_{it}^2 + \beta_2 Temp_{it} \cdot Irr_i + \beta_3 Temp_{it} + \beta_4 Prec_{it}^2 + \beta_5 Prec_{it} \cdot Irr_i + \beta_6 Prec_{it}\right] \tag{5}$$

$$\boldsymbol{\beta}\mathbf{X}_{it}^{3} = \left[\beta_1 Temp_{it}^2 + \beta_3 Temp_{it} + \beta_4 Prec_{it}^2 + \beta_6 Prec_{it} + \beta_7 Pest_{it} + \beta_8 Fert_{it}\right] \tag{6}$$

Finally, the simplest set of explanatory weather variables include only weather factors:

$$\boldsymbol{\beta}\mathbf{X}_{it}^{4} = \left[\beta_1 Temp_{it}^2 + \beta_3 Temp_{it} + \beta_4 Prec_{it}^2 + \beta_6 Prec_{it}\right] \tag{7}$$

Specification search

We follow the General-to-Specific approach[51] both in terms of the selection of the explanatory variables and the statistical models being estimated. With regard to the statistical models discussed above, our methodology goes from the most general to the most specific model, by implementing models

1) with both country-specific quadratic time trends and common time effects, (1) above;
2) only country-specific quadratic time trends, (2) above;
3) only common time effects, (3);
4) models where data are pooled either across time or countries.

With regard to explanatory variables used in the estimation, we move from the most general set, i.e. $\mathbf{X}_{it}^{1}$, to the most specific, i.e. $\mathbf{X}_{it}^{4}$. During the specification search, a model is considered to be congruent to the underlying data generating process of crop yield if

1) the relationship between yield and temperature has an inverted-U functional shape;
2) coefficients on pesticides, fertilizers and irrigation indicators are statistically significant;
3) the optimal temperature observed in countries with intensive irrigation systems is higher than that in countries where irrigation use is low;
4) the impact of pesticides on crop yield is positive.

Data for irrigation, pesticides and fertilisers are observed for the agricultural sector as a whole rather than for a specific crop. In addition, these variables are available for a limited number of countries and time periods compared the crop yield and weather. For these reasons, condition 2) above is imposed, so that these variables are retained only if they contribute to explaining the crop yield in a statistically significant fashion. We therefore use statistical significance to discern whether variables observed for the whole agricultural sector can be used as a proxy for the impact of intensification and management practices for the specific crop at hand, therefore tackling the limitation that crop-specific fertilisers, pesticides and irrigation data are not available at global scale. As a further criterion to discern sensible impact of irrigation and pesticides we require optimal temperature observed in the countries with intensive irrigation systems to be higher than the optimal level in countries where irrigation use is low[11] – see condition 3 above. A positive relationship between the use of pesticides and protection of crop quality and yield is well established[54], so that we explicitly require coefficient on pesticides being positive – condition 4. Yet, evidence on the relationship between the use of fertilisers and crop yield is less conclusive[55], so that we do not impose a similar requirement on the coefficient of fertilisers. Condition 1) above arises from the fact that it reflects a plausible assumption for the growing conditions of crops, and is a common assumption in economic studies and increasingly used in the econometric crop yield literature[10,12] to indicate that crops are benefited by moderate weather changes while are damaged under extreme circumstances. The effect of precipitation is harder to identify compared to the temperature effect, with precipitation coefficients being non-statistically significant[21]. Also climate models disagree on the sign of precipitation[56], an indication of the uncertainty surrounding the impact of this factor on yield. For this reason, we do not impose condition 1) for precipitation, with our procedure limited to dropping the quadratic term when the coefficient is positive.

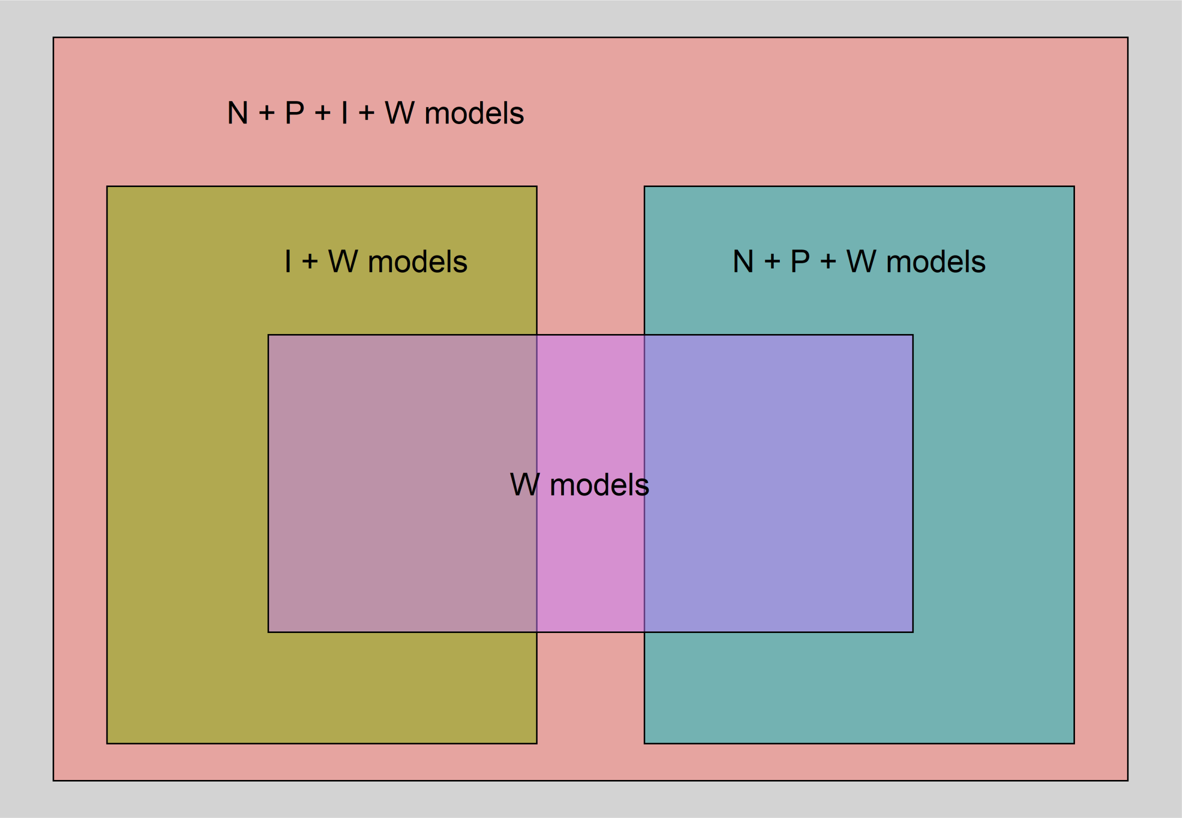
Our specification search is therefore the following.

1) We run each statistical model described above with the set of variables in equation (4) and assess the suitability of the estimated models, i.e. the $N + P + I + W$ models in Figure 7 (where N, P, I, W stand for Nitrogen/Fertilisers, Pesticides, Irrigation and Weather respectively), based on the conditions above.

2) If none of the models satisfies the search criteria above, we simplify the set of control variables by estimating the (I + W) models, the (N + P + W) models dropping either N or P if one contradicts conditions above, and the W models in Figure 7, in this order.

3) As soon as the applicable conditions are met, we stop the search procedure and select the final model. This occur in the case of all crops.

Models delivered by this specification search are comparable to those in the literature when assessed based on the amount of variation in the crop yield explained by the models. For instance, our adjusted R^2 is 57% and 35% for maize and sorghum - which are comparable, for instance, to 47% and 29%[16].



[FIGURE 7]

Figure 7. Schematic representation of the relationship between the set of explanatory variables used in this study. $N + P + I + W$ models indicate models incorporating X_{it}^1 above; $I + W$ models incorporating X_{it}^2; $N + P + W$ models incorporating X_{it}^3; and W models incorporating X_{it}^4.

Marginal effect and optimal level of weather factors

For the final models identified through the specification search described above, we computed the optimal level of each weather factor, taking into account interaction with the irrigation dummies. In the case of temperature, as an example, the optimal temperature for countries where irrigation use is deemed negligible can be computed as $V_{TEMP} = -\frac{\beta_3}{2\beta_1}$, whereas for countries using high irrigation, the optimal level is equal to $V_{TEMP-IRR} = -\frac{(\beta_2+\beta_3)}{2\beta_1}$. For each model, we computed the coefficient of determination (R^2) with and without adjusting for the variables used in the regression. Standard errors robust to heteroscedasticity and serial correlation were estimated to assess the significance of the coefficients in the models, as shown in Supplementary Table 1.

In addition, for each model we computed the effect of temperature and precipitation in relation to a change of 1°C and 10 mm. As we estimated a quadratic relationship, the effect varies across the level of the weather factor at which the effect is computed. As an example, the impact of a 1°C temperature increase starting from the level T_0 for countries where irrigation use is deemed negligible can be computed as:

$$ME_{TEMP}^{1°C} = 2\beta_1 + \beta_3 T_0$$

while for countries using high irrigation, the impact of a 1°C temperature increase is equal to:

$$ME_{TEMP}^{1°C} = 2\beta_1 + (\beta_2 + \beta_3)T_0$$

The impact of a temperature increase different from 1°C can be obtained by simply multiplying $\mathrm{TE}_{\mathrm{TEMP}}^{1°\mathrm{C}}$ by any specific increase in temperature. Supplementary Table 1 reports the marginal effect evaluated at the global mean, observed over the 1986 and 2012. In Supplementary Table 1, we also present the impact observed in correspondence of a change in temperature and precipitation equal to the average standard deviation, computed by averaging the standard deviation observed in each country in the sample used in this study, so as to obtain a global average of the standard deviation of the weather factors observed in each country. This has been computed at the global mean.

Data availability

The data used in this study are available through this repository: DOI: 10.5522/04/12768425.

Code availability

The scripts used in the estimation of the models and the production of the figures displayed in the paper is available through this repository: DOI: 10.5522/04/12768425.

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Contributions

All authors developed the research methodology. P.A., V.L. and C.R. collected the data and computed the variables used in the estimation. P.A. and C.R. implemented the estimation. All authors contributed to writing up results.

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Ethics declaration

Competing interests

The authors declare no competing interests.

Supplementary information

Historic variation in yields and model performance.
Effect of weather, irrigation, pesticides and fertilizers on crop yields.
Supplementary Figure 1-3.
Supplementary Table 1.

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Impacts of rising temperatures and farm management practices on global yields of 18 crops

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Supplementary information

Historic variation in yields and model performance.

There is considerable diversity in the average crop yields, observed over 1986-2012 across countries. The average yield of maize, as an example, varies by two orders of magnitude, between 265 kg/ha (Botswana) and 16,000 kg/ha (Israel), with yields above 10,000 kg/ha recorded in Israel, Jordan, Belgium and New Zealand. For each crop, there tends to be a limited number of countries with yield considerably higher than the rest, manifesting as a long right tail in the distributions of crop yield – see Supplementary Figure 1. There is also diversity in the pattern of crop yield across time, reflecting the different evolution of environmental, social and economic growing conditions occurring across time in different countries, as shown for the 5 biggest producers (based on mean production during 1986-2012) in Supplementary Figure 2. In some cases, crop yields levels differ across countries but share a common pattern across time while for some other crops, there is no consistent trend across countries.

We model the relationship between yield and its determinants, focusing on temperature, precipitation, pesticides, fertilisers and irrigation, separately for the 18 crops we consider. We implement panel data models to take into account within country and across-countries variation but also similarities, as well as unobserved diversity through fixed or random effects. We also incorporate country specific time trends to proxy for factors that could positively (e.g. technological advance) or negatively (e.g. soil erosion) affect yield patterns and estimate models producing credible estimates while partially capturing the variation in the data either across countries or across time, as discussed in Methods.

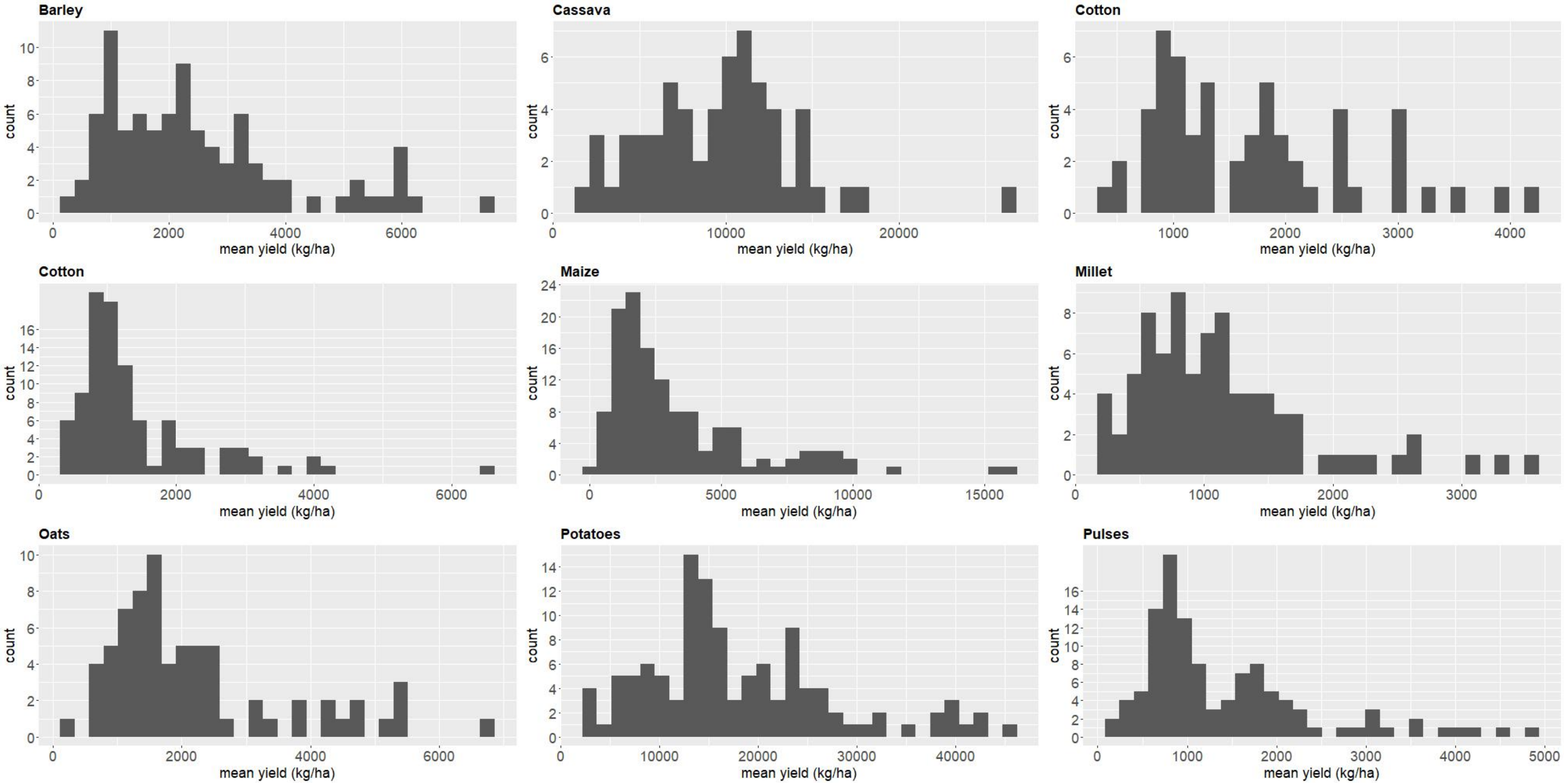
We extend established approaches for modelling the effects of climate on crop yields by accounting for additional factors affecting crop productivity (fertilisers, pesticides and level of irrigation), and covering a larger number of crops, all studied for the first time at the global level (Methods). Estimated models studied explain a considerable part of the yield based on the computed coefficient of determination (R^2) - higher than 80% in the case of cotton, pulses, potatoes, rice, sunflower and wheat, and between 50 and 70% in the case of cassava, groundnuts, maize and oats.

Effect of weather, irrigation, pesticides and fertilizers on crop yields.

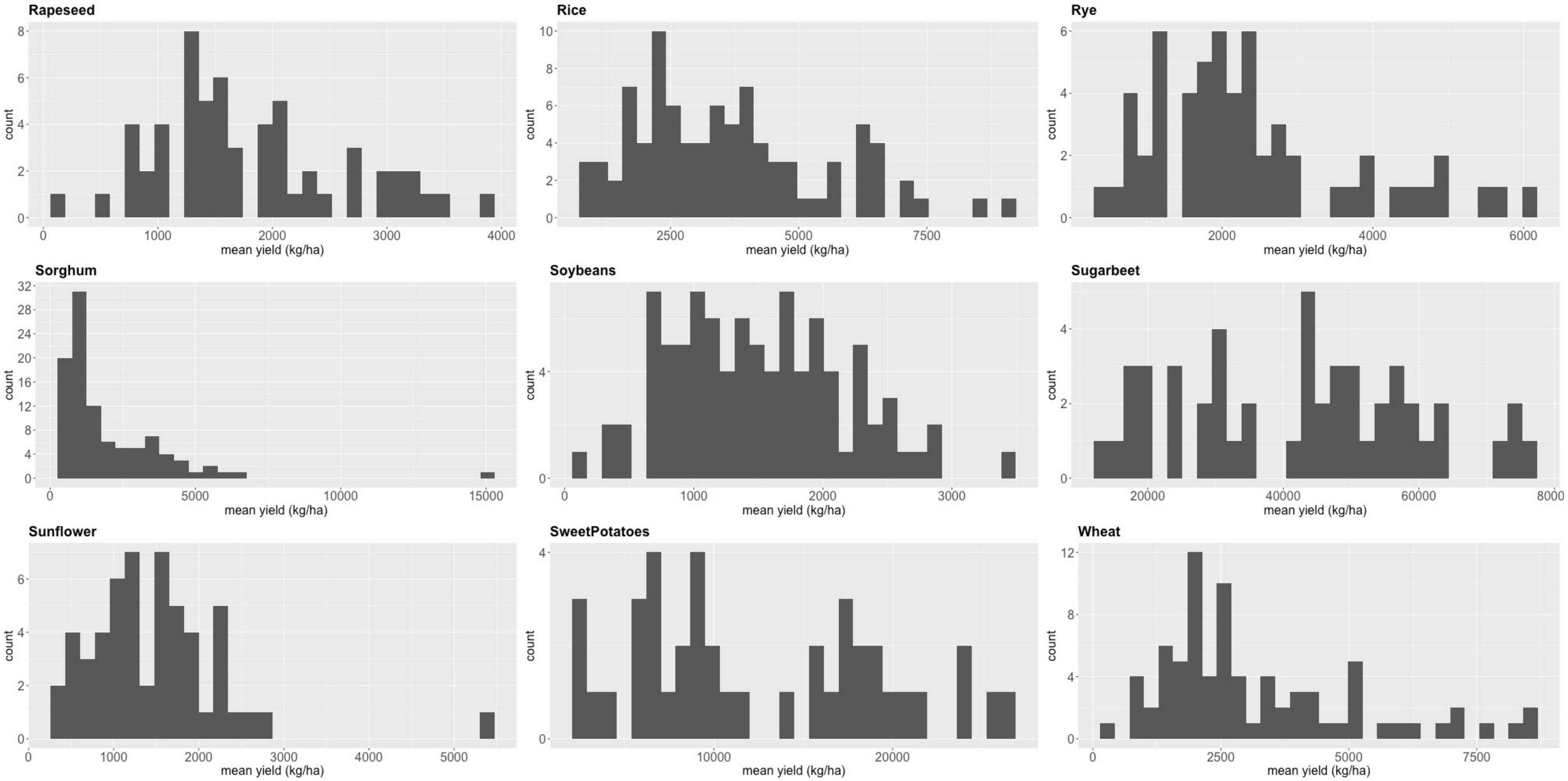
We estimated an inverted U-shaped relationship between temperature and crop yields for all 18 crops, with the computed values for the optimal temperature reflecting credible conditions of crop production (Supplementary Table 1). Each plot in column A of Figure 2 - Figure 6 reports the marginal effect of temperature estimated at the global mean and +/- 4°C. As agronomy differs between countries and crops in some instances we provide estimates for high inputs with irrigation and low input systems. As one can see in Figure 1, in the models including irrigation, the negative impact of temperature is mitigated so that the optimal level of temperature is higher in those countries with intensive irrigation systems. As an example, in the case of maize, optimal growing temperature is about 15°C in case of low irrigation and 18.5°C for countries with high irrigation – see Figure 3. This allows maize to develop higher resilience to temperature, which reduces the marginal effect on yield from -2.6% to -1.1% evaluated at the global mean. Moreover, in the case of wheat, intensive irrigation appears to turn the negative impact (-2.4%) into positive (3.3%), as optimal temperature increases from about 15 °C, when irrigation does not play an important role, to 20 °C when it is of high use.

With regard to the functional relationship between crop yield and precipitation, an inverted U-shaped relationship is estimated for 8 of the 18 crops. For the remaining crops, the effect appears to be linear, with both negative and positive effects observed across crops. The use of pesticides and fertilisers positively impacts crop yield, with these factors indicating intensification of crop production and improved management. More specifically, according to our results, an increase of one kg/ha of pesticides raises the yield of about half the crops modelled here, in the range between 4% in the case of sugar beet and 14% of potatoes, while in the case of the other crops, this factor was dropped as being non-statistically significant or providing counterintuitive results. An increase of one kg/ha of fertilisers increases the yield between 0.2% in the case of sugar beet and 0.6% in the case of sunflower. Detailed results, including all estimated coefficients, are shown in Supplementary Table 1. Distribution of pesticides and fertilisers can be seen in Supplementary Figure 3.

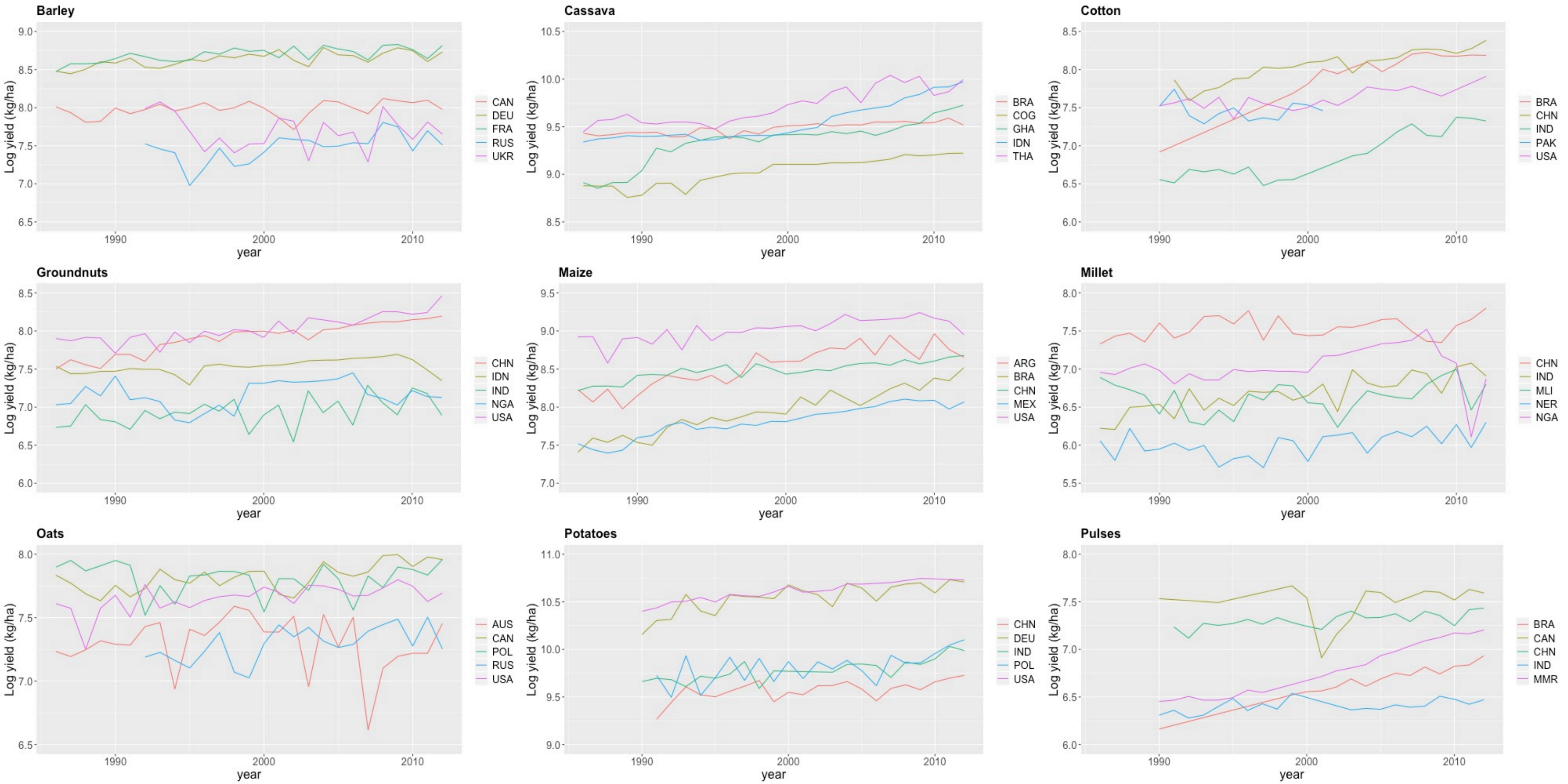
Further details on the optimal level (indicated by 'V') and the marginal effect (indicated by 'ME') of temperature and precipitation can be found in Supplementary Table 1. The marginal effect represents the percentage change in crop yield in response to an increase in temperature by 1 °C or 1 standard deviation, and an increase in precipitation by 10mm or 1 standard deviation, evaluated at the global mean. Irrigation implies higher optimal temperature values and higher resistance to temperature, so that the negative impact of temperature on the yield is contained. As an example, temperature increases are beneficial for maize up to the optimal temperature of 14.6 °C, with a marginal impact (of 1 °C change in temperature) at the global mean of about -3%. However, the optimal level of temperature is higher (18.5°C) in countries with high irrigation, and the marginal impact at the global mean smaller (-1%) although still negative. Similarly, the optimal level of temperature for cassava is about 20.5 °C and the marginal impact at the global mean -1.4% while in presence of high levels of irrigation, the optimal temperature level rises to 25.8 °C and the marginal impact at the global mean is 0.6%.



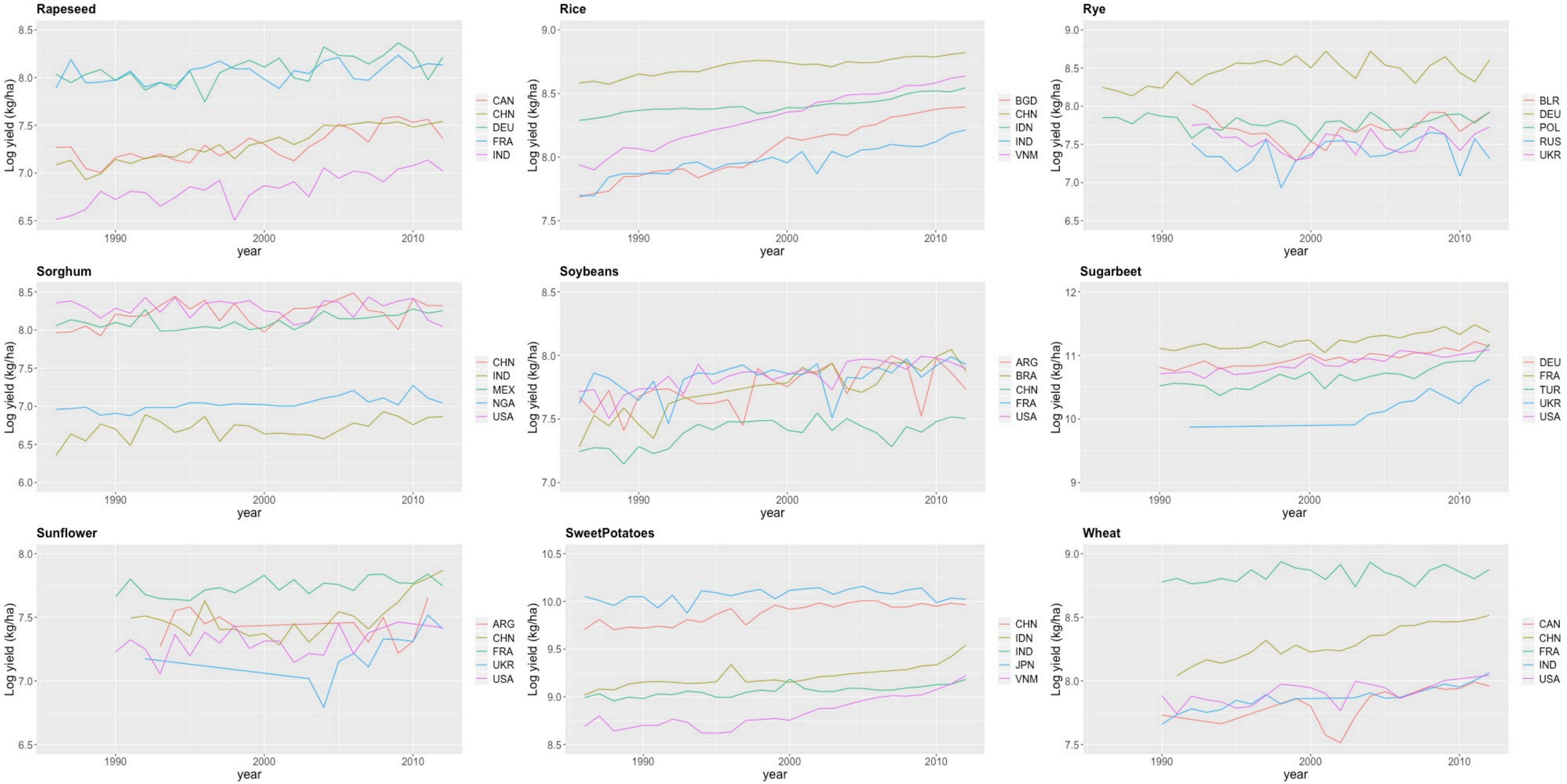
Supplementary Figure 1a. Distribution of country average yields, computed over the 1986-2012 time period. Figures have been computed over the 1986-2012 period from FAOSTAT commodity balance data. The x-axis depicts the average crop yield (measured in kg/ha), and the y-axis the frequency of each value being observed in the dataset.



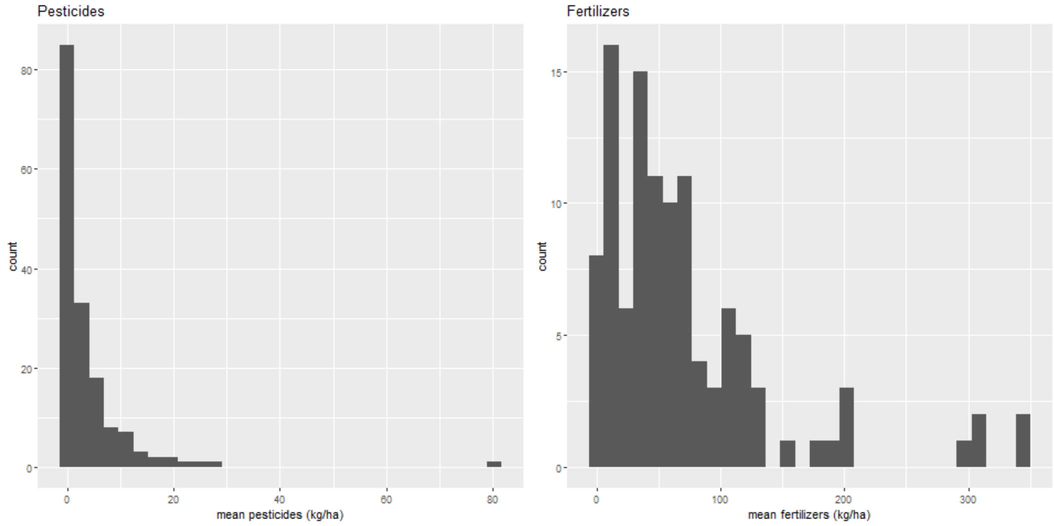
Supplementary Figure 1b. Distribution of country average yields, computed over the 1986-2012 time period. Further note can be found in the caption of Supplementary Figure 1a.



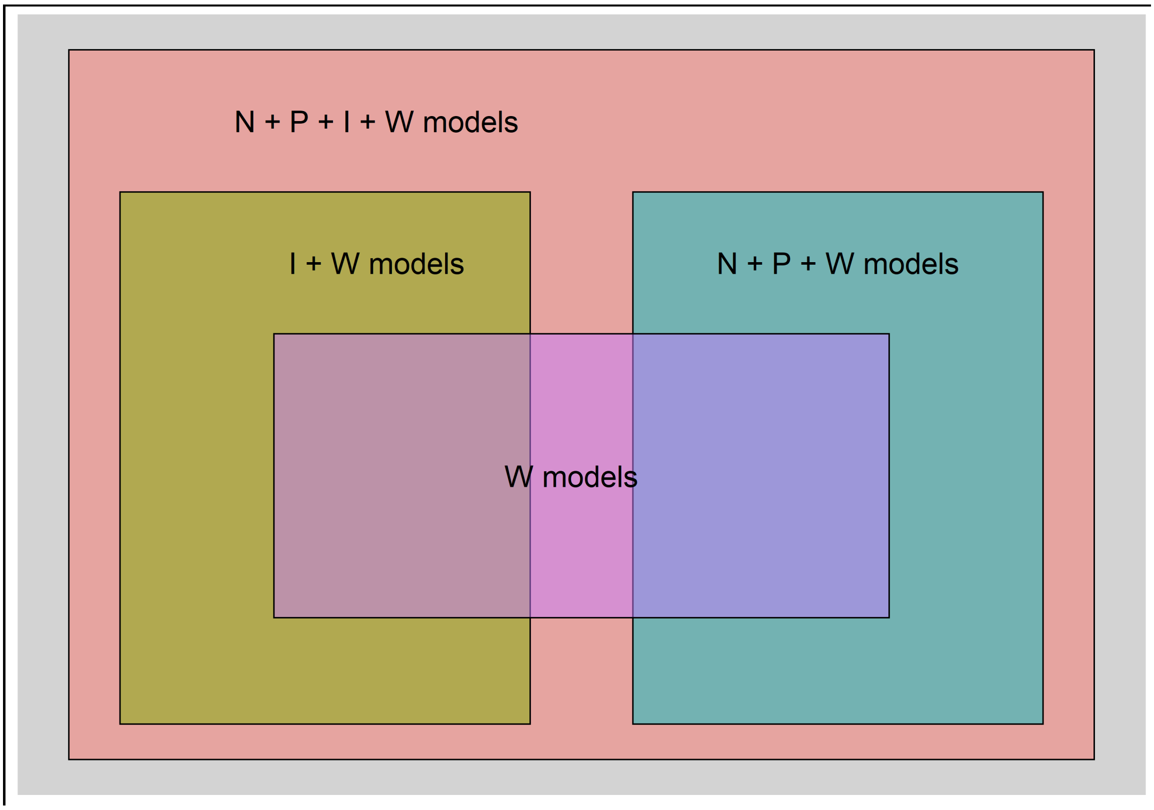
Supplementary Figure 2a. **Pattern of historical yields for the 5 biggest producers**. The acronyms in the figure indicate the following countries: Argentina (ARG), Australia (AUS), Brazil (BRA), Canada (CAN), China (CHN), Congo (COG), Germany (DEU), France (FRA), Germany (DEU), Ghana (GHA), Indonesia (IDN), India (IND), Mali (MLI), Mexico (MEX), Myanmar (MMR), Niger (NER), Nigeria (NGA), Pakistan (PAK), Poland (POL), Russia (RUS), Thailand (THA), Ukraine (UKR) and Unites States of America (USA).



Supplementary Figure 2b. **Pattern of historical yields for the 5 biggest producers**. The acronyms in the figure indicate the following countries: Argentina (ARG), Bangladesh (BGD), Belarus (BLR), Brazil (BRA), Canada (CAN), China (CHN), Germany (DEU), France (FRA), Indonesia (IDN), India (IND), Japan (JPN), Mexico (MEX), Nigeria (NGA), Poland (POL), Russia (RUS), Turkey (TUR), Ukraine (UKR), Vietnam (VNM)and Unites States of America (USA).



Supplementary Figure 3. Distribution of average pesticides (left) and fertilizers (right). Figures have been computed over the 1986-2012 period. The x-axes depict the average use of pesticides (kg/ha) and fertilizers (kg/ha) and the y-axis the frequency of each value being observed in the dataset..



Supplementary Figure 4. Schematic representation of the relationship between the set of explanatory variables used in this study. $N + P + I + W$ models indicate models incorporating X_{it}^{1} in the Methods; $I + W$ models incorporating X_{it}^{2}; $N + P + W$ models incorporating X_{it}^{3}; and W models incorporating X_{it}^{4}

	Barley	Cassava	Cotton	Groundnuts	Maize	Millet
Temp	0.072**	0.079	0.142	0.251*	0.056	0.292
Temp^2	-0.002**	-0.002***	-0.003	-0.006**	-0.002**	-0.007
Prec	-2.213E-04	3.8E-04	7.03E-05	-2.7E-04	-2.0E-04	-9.6E-04
Prec^2			-1.91E-06			
Temp Irr		0.020***		0.016**	0.015**	
Prec Irr				0.000		
Pest						
Fert						
V Temp	15.50	20.58	22.81	21.90	14.56	19.85
V Temp Irr		25.82		23.28	18.48	
V Prec			18.38			
V Prec Irr						
ME Temp (1°C)	-0.6%	-1.4%	0.76%	-1.7%	-2.6%	-2.9%
ME Temp Irr (1°C)		0.6%		-0.1%	-1.1%	
ME Prec (10mm)	-0.22%	0.4%	-0.34%	-0.3%	-0.2%	-1.0%
ME Prec Irr (10mm)				-0.1%		
ME Temp (1sd)	-0.34%	-0.3%	0.32%	-0.6%	-1.1%	-1.4%
ME Temp Irr (1sd)		0.1%		0.0%	-0.5%	
ME Prec (1sd)	-0.30%	0.7%	-0.51%	-0.5%	-0.4%	-1.7%
ME Prec Irr (1sd)				-0.2%		
R^2	0.24	0.68	0.86	0.51	0.60	0.85
R^2_{adj}	0.17	0.66	0.82	0.46	0.57	0.81
N	2179	1614	1455	2553	3412	1959
n	88	60	57	98	132	82
Wald test (Chi-square, p-value)	5.98 0.11	13.22 0.01	0.43 0.98	22.37 0.00	12.82 0.01	1.36 0.72

Supplementary Table 1a. Estimated models for the crops modelled in this study. Estimation is based on robust standard errors when the model accounts for within and across countries variation. ***, **, * indicate statistical significance at the 1%, 5% and 10% level, respectively. V Temp, ME Temp and V Prec, ME Prec represent vertices and marginal effects for temperature and precipitation respectively. V Temp Irr, ME Temp Irr, V Prec Irr and ME Prec Irr indicate vertices and marginal effects for temperature and precipitation in the high irrigation countries. Marginal effect of temperature and precipitation, evaluated at the sample average, are computed in response to a 1°C, 10mm and average 1 standard deviation (1sd), averaged across countries, of the weather factors they refer to. N and n denote the number of observations and the number of countries, respectively. The joint significance of weather factors is assessed through a Wald test.

	Oats	**Potatoes**	**Pulses**	**Rapeseed**	**Rice**	**Rye**
Temp	0.042	0.065	0.161	0.100***	0.606	0.059
Temp^2	-0.002	-0.001	-0.006	-0.005***	-0.014	-0.006**
Prec	4.0E-04	-0.002	8.2E-05	0.010	0.004	0.007**
Prec^2	-6.2E-07		-5.4E-06	--9.7E-06	-9.9E-06	
Temp: Irr						0.066**
Prec: Irr						-0.014***
Pest		0.142***	0.064**		0.134***	
Fert						
V Temp	13.43	23.59	13.29	9.41	21.67	4.89
V Temp Irr						10.36
V Prec	318.88		7.61	499.29	223.73	
V Prec Irr						
ME Temp (1C)	-0.5%	1.5%	-8.7%	0.02%	-2.8%	-4.2%
ME Temp Irr (1C)						2.4%
ME Prec (10mm)	0.3%	-1.6%	-1.1%	8.5%	1.6%	7.3%
ME Prec Irr (10mm)						-6.8%
ME Temp (1sd)	-0.3%	0.6%	-4.6%	0.0%	-1.0%	-2.8%
ME Temp Irr (1sd)						1.6%
ME Prec (1sd)	0.4%	-2.5%	-2.2%	7.6%	3.2%	6.7%
ME Prec Irr (1sd)						-6.2%
R^2	0.52	0.86	0.94	0.36	0.88	0.32
R^2_{adj}	0.48	0.83	0.91	0.32	0.85	0.25
N	1704	1661	1629	1334	1209	1375
n	70	116	114	58	90	58
Wald test (Chi-square, p-value)	2.36 0.67	1.27 0.74	19.02 0.00	30.27 0.00	4.35 0.36	24.15 0.00

Supplementary Table 1b. Estimated models for the crops modelled in this study. Description of the contents of the table can be seen in the caption of Supplementary Table 1a

	Sorghum	**Soybeans**	**Sugarbeet**	**Sunflower**	**Sweet Potatoes**	**Wheat**
Temp	0.101	0.115	0.130	0.121	0.160	0.147**
Temp^2	-0.002	-0.002	-0.004	-0.003	-0.004	-0.005**
Prec	2.9E-04	2.9E-04	0.005	0.001	0.005	0.010***
Prec^2	-9.8E-07		-4.1E-05		-2.8E-05	-4.1E-05**
Temp: Irr						0.057**
Prec: Irr						-0.005
Pest			0.043**	0.120***	0.052*	0.127***
Fert			1.651**	6.033**	3.494**	-2.633**
V Temp	27.58	25.84	16.21	20.62	22.77	14.59
V Temp Irr						20.18
V Prec	147.60		61.22		96.59	117.11
V Prec Irr						55.22
ME Temp (1C)	1.9%	2.2%	0.6%	0.8%	1.0%	-2.4%
ME Temp Irr (1C)						3.3%
ME Prec (10mm)	0.1%	0.3%	0.0%	0.9%	-1.3%	3.5%
ME Prec Irr (10mm)						-1.5%
ME Temp (1sd)	0.8%	0.9%	0.3%	0.4%	0.3%	-1.3%
ME Temp Irr (1sd)						1.8%
ME Prec (1sd)	0.1%	0.6%	0.0%	1.2%	-2.4%	4.7%
ME Prec Irr (1sd)						-2.1%
R^2	0.43	0.01	0.41	0.85	0.34	0.92
R^2_{adj}	0.35	0.01	0.32	0.81	0.23	0.88
N	2450	2196	757	765	582	1208
n	99	91	49	54	41	78
Wald test (Chi-square, p-value)	3.26 0.51	4.35 0.23	13.52 0.01	0.48 0.92	3.82 0.43	28.65 0.00

Supplementary Table 1c. Estimated models for the crops modelled in this study. Description of the contents of the table can be seen in the caption of Supplementary Table 1a.

References