Disentangling the separate and confounding effects of temperature and precipitation on global maize yield using machine learning, statistical and process crop models

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Abstract
Temperature impacts on crop yield are known to be dependent on concurrent precipitation conditions and vice versa. To date, their confounding effects, as well as the associated uncertainties, are not well quantified at the global scale. Here, we disentangle the separate and confounding effects of temperature and precipitation on global maize yield under 25 climate scenarios. Instead of relying on a single type of crop model, as pursued in most previous impact assessments, we utilize machine learning, statistical and process-based crop models in a novel approach that allows for reasonable inter-method comparisons and uncertainty quantifications. Through controlling precipitation, an increase in warming of 1 °C could cause a global yield loss of 6.88%, 4.86% or 5.61% according to polynomial regression, long short-term memory (LSTM) and process-based crop models, respectively. With a 10% increase in precipitation, such negative temperature effects could be mitigated by 3.98%, 1.05% or 3.10%, respectively. When temperature is fixed at the baseline level, a 10% increase in precipitation alone could lead to a global yield growth of 0.23%, 1.43% or 3.09% according to polynomial regression, LSTM and process-based crop models, respectively. Further analysis demonstrates substantial uncertainties in impact assessment across crop models, which show a larger discrepancy in predicting temperature impacts than precipitation effects. Overall, global-scale assessment is more uncertain under drier conditions than under wet conditions, while a diverse uncertainty pattern is found for the top ten maize producing countries. This study highlights the important role of climate interactions in regulating yield response to changes in a specific climate factor and emphasizes the value of using both machine learning, statistical and process crop models in a consistent manner for a more realistic estimate of uncertainty than would be provided by a single type of model.

1. Introduction
Quantifying climate change impacts on crop yield is critical for ensuring food security, and numerous studies have been conducted to assess the effects of climate variability and extremes (Asseng et al 2011, Lobell et al 2011a, Rötter et al 2012, Wheeler and von Braun 2013, Ray et al 2015, Lesk et al 2016, Schaubberger et al 2017, Zampieri et al 2017, Zhao et al 2017, Hlaváčová et al 2018, Leng and Hall 2019, Vogel et al 2019). Among others, temperature and precipitation are the major climate factors dominating crop growth and yield (Lobell and Field 2007, Deryng et al 2011, Lobell et al 2011b, Butler and Huybers 2012, Liu et al 2016, Zhao et al 2017, Hlaváčová et al 2018, Leng 2019). In general, high temperature often leads to a yield loss by shortening the reproductive phase, enhancing leaf senescence, and causing stomata closure (Hawkins et al 2013, Hlaváčová et al 2018), while precipitation exerts an
influence on crop yield mainly through altering soil moisture conditions (Lobell et al. 2014).

Besides the direct effects on plant physiology and photosynthesis, a high temperature could increase water demand and decrease soil water supply via enhanced evapotranspiration, which together leads to elevated water stress for crop growth with negative impacts on yield formation (Siebert et al. 2017). Therefore, precipitation as a proxy of soil moisture condition is likely an important factor that can significantly modulate temperature–yield relations (Hatfield and Prueger 2015, Leng 2019). Indeed, temperature impacts on yield are shown to be enhanced under drought conditions (Lobell et al. 2014, Zipper et al. 2016), while alleviated impacts are reported under irrigated conditions (Troy et al. 2015, Leng 2017a, 2017b). However, studies on disentangling the effects of temperature from precipitation are lacking, which precludes the effective design of adaptation and mitigation strategies under future warming.

Field experiments can allow for the examination of the local effect of a single climatic factor on yield (Ainsworth and Long 2005, Ottman et al. 2012, Kravchenko et al. 2017), but cannot be robustly extrapolated and extended to regional scales. For large-scale investigations, statistical and process crop models are indispensable tools and have been widely used to quantify global and regional climate impact on crop yield (Schlenker and Roberts 2009, Rosenzweig et al. 2014, Ray et al. 2015). For example, Lobell et al. (2011a) investigated the African maize yield response to high temperatures using a statistical model, and found an elevated temperature impact under drought conditions. Using a partial regression model, Leng (2019) showed that about 27% of the observed temperature–yield relationship for US maize is contributed by concurrent precipitation changes. Schauberger et al. (2017) compared temperature impacts on US maize yield under irrigated and rainfed conditions based on eight process crop models, and found that water deficits have exacerbated yield losses under high temperatures. Given that statistical and process crop models have their own strengths and weaknesses, using multiple types of crop models for climate impact assessment has been proposed in recent studies (Lobell and Asseng 2017, Roberts et al. 2017, Leng and Hall 2020, Yin and Leng 2020, Leng 2021). However, existing inter-method studies are often based on crop model simulations fed with inconsistent climate scenarios and parameters (Liu et al. 2016, Lobell and Asseng 2017, Zhao et al. 2017), thus prohibiting reasonable comparisons between statistical and process models. To date, a robust multi-model global assessment of the separate and confounding effects of temperature and precipitation on crop yield are still lacking.

To fill the gap, we aim to disentangle the separate and confounding effects of temperature and precipitation on global maize yield using multiple types of crop models. Besides statistical and process crop models, we develop a machine learning model which has recently emerged as a powerful tool for assessing climate impact on crop yield (You et al. 2017, Zhang et al. 2019, Kang et al. 2020, Schwalbert et al. 2020, Cao et al. 2021, Shahhosseini et al. 2021). Unlike traditional statistical models, machine learning does not require prior knowledge of climate–yield relations and can thus well complement data-driven model analysis. Specifically, the following scientific questions are addressed in this study: (a) How does global maize yield respond to various temperature change levels after controlling precipitation effects? (b) How does precipitation regulate temperature impacts on maize yield across the globe? (c) How much uncertainty would be expected from the choice of impact models? Instead of exploring the uncertainty of a specific model, which could arise from its choice of input, parameters and etc, we focus our analysis on the difference and similarity between different types of crop models. That is, the uncertainty is defined as the range of predicted yield responses to climate change scenarios between machine learning, statistical and process crop models. Here, 25 climate scenarios (five temperature × five precipitation change intervals) are developed and consistently fed to machine learning, statistical and process models. Our inter-model comparisons advance previous studies in that all types of crop models are driven with the same climate scenarios so that reasonable comparisons can be achieved.

2. Materials and methods

2.1. Observed climate and census yield data

Global monthly gridded temperature and precipitation data are obtained from the Agricultural NASA Modern-Era Retrospective Analysis for Research and Applications (AgMERRA) (Ruane et al. 2015), which is developed specifically for agricultural modeling and climate impact assessment. Census data on annual maize yields of the globe and the top ten producing countries are obtained from the Food and Agriculture Organization of the United Nations (FAO) FAOSTAT database (www.fao.org/faostat/en/#data/QC). The gridded monthly climates at a spatial resolution of 0.5° × 0.5° are averaged over the growing seasons from a crop calendar map (Sacks et al. 2010), based on which annual time series of growing-season mean temperature and precipitation are derived. To be consistent with the scale of FAO census yield, gridded growing season climates are further aggregated to the global and country scales, with weights based on the harvest area identified by the MIRCA2000 map (Portmann et al. 2010). The regional mean growing season temperature and precipitation are used to develop statistical and machine
learning models that link yield variability empirically to climate variations, as detailed in section 2.3.

2.2. Process-based crop models

In this study, six process-based crop models including CARAIB (CARbon assimilation in the biosphere), EPIC-TAMU (environmental policy integrated climate model by Texas A&M University), JULES (the joint UK land environment simulator), LPJ-GUESS (Lund-Potsdam-Jena general ecosystem simulator), LPJmL (Lund-Potsdam-Jena managed land), and pDSSAT (parallel decision support system for agrotechnology transfer), (table 1) are adopted to simulate climate impacts on global maize yield. These models are run at a spatial resolution of 0.5° × 0.5° for the period 1980–2010 driven with the observed climate AgMERRA (hereafter referred to as the baseline experiment), and several sensitivity experiments are conducted for each model under various temperature and precipitation perturbation scenarios (Franke et al 2020). Specifically, uniform change factors are applied to the observed temperature and precipitation time series to derive climate scenarios, which are further fed to the process-based models. Here, five temperature (−1 °C, 0 °C, +1 °C, +2 °C, +3 °C) and five precipitation perturbation levels (−20%, −10%, 0%, +10%, +20%) are examined, leading to a total of 25 sensitivity simulations for our analysis. The baseline and sensitivity simulations are conducted under the Global Gridded Crop Model Intercomparison (GGCMI) Phase 2 project, as part of the Agricultural Model Intercomparison and Improvement Project (AgMIP). Since our focus is on the interactions between temperature and precipitation, the CO₂ concentration levels in the sensitivity simulations are fixed at the same levels as the baseline. Details on the model setup, inputs and experimental protocols can be referred to in the work by Franke et al (2020).

2.3. Statistical model and machine learning

Besides process models, we develop statistical and machine learning models trained with the observed climate and yield time series (see section 2.1). Here, the polynomial regression is constructed following the literature (Hawkins et al 2013, Ray et al 2015), while the long short-term memory (LSTM) does not need to assume a specific form of climate-yield functions and can thus well complement data-driven analysis. LSTM is a special kind of recurrent neural network (RNN) and can process a sequence of inputs through direct connections (LeCun et al 2015). Due to its capability to capture complex nonlinear relationships between independent and dependent variables (Malhotra et al 2015), LSTM has been widely

| Model       | Heat stress type | Water stress type | Spatial scale of calibration | Parameters for calibration | Crop cultivars | Key citations                  |
|-------------|------------------|-------------------|------------------------------|----------------------------|----------------|---------------------------------|
| CARAIB      | T1               | W1                | Uncalibrated                 | NA                         | GDD, BT        | Dury et al (2011), Pirttioja et al (2015) |
| EPIC-TAMU   | T2               | W2; W3            | Grid cell level              | HIpot                      | GDD, 2cultivars for maize | Ozaurralde et al (2006), Osborne et al (2015), Williams et al (2017), Williams and Falloon (2015) |
| JULES       | T3               | W4                | Uncalibrated                 | NA                         | GDD            | Elliott et al (2014), Jones et al (2003) |
| LPJ-GUESS   | NA               | W2                | Uncalibrated                 | NA                         | GDD, BT        | Lindeskog et al (2013), Qin et al (2015) |
| LPJmL       | NA               | W2                | National                     | LAImax; Hl; xta            | GDD, BT        | von Bloh et al (2018)           |
| pDSSAT      | T4               | W5                | Field scale                  | NA                         | GDD and/or latitude, 2–3 for each cell—fixed |                                |

Notes: NA where not applicable.
T1: heat stress affects photosynthesis and respiration; T2: vegetative (source); T3: aggregated degree-day sum that affects phenology; T4: vegetative, reproductive organ (sink), number of grains (pod) set during the flowering period. W1: water stress affects photosynthesis, phenology and heterotrophic respiration; W2: ratio of supply to demand of water; W3: soil available water in root zone (a balance of the two based on input of 0–1); W4: water stress affects the photosynthesis and leaf maintenance respiration; W5: ratio of soil available water in the root zone to demand water. Hlpot: potential harvest index; LAImax: maximum leaf area index (LAI) under unstressed conditions; Hl: harvest index; xta: factor for scaling leaf-level photosynthesis to stand level. GDD: simulate crop growing degree days (GDDs) requirement according to estimated annual GDDs from daily temperature; number of cultivars; BT: base temperature computed based on past climate.
used for crop yield predictions (You et al. 2017, Sun et al. 2019, 2020, Kang et al. 2020, van Klompenburg et al. 2020).

Instead of including as many as possible influencing factors for accurately predicting yield values, we focus on the separate and compounding effects of two climate factors (i.e. temperature and precipitation), which are recognized as the major climatic determinants of global yield variability (Lobell et al. 2011b, Ray et al. 2015, Zhao et al. 2017). Following previous studies (Hawkins et al. 2013, Ray et al. 2015), growing-season mean temperature, precipitation and their interaction term are used as the climate predictors, while a year term is included to represent the trend component of yields in both the statistical and machine learning models. In particular, the polynomial regression model is trained with observed yield as the dependent variable and climate predictors and a year term as the independent variables, as shown in equation (1)

\[
\text{Yield}_i = a_0 + a_1 \times T_p + a_2 \times P_p + a_3 \times Y_p + a_4 \times T_p \times P_p + \epsilon_{a,i},
\]

where \(T_p\), \(P_p\) and \(Y_p\) are the growing-season mean temperature, precipitation and year term for the year \(y\), respectively; \(a_0\) and \(a_1\) are the intercept and coefficients, respectively; \(\epsilon_{a,i}\) is the error term. The LSTM model is trained using the same dependent and independent variables, but without specification of the form of climate-yield relations (equation (2))

\[
\text{Yield}_p = \text{LSTM}(T_p, P_p, Y_p),
\]

where LSTM denotes the long short-term memory model, \(T_p\), \(P_p\), \(Y_p\) are the temperature, precipitation and year term for the year \(y\), respectively.

In this study, we randomly choose 80% of the dataset (i.e. 24 years of data) for training the statistical and LSTM models, while the remaining 20% of samples (i.e. 6 years of data) are used for validations. This process is repeated 100 times to test the robustness of statistical and LSTM models, and the parameters with the best performance are selected for assessing the impacts of climate change on crop yield. Model performances are assessed based on several evaluation metrics, including the coefficient of determination (\(R^2\)), relative bias (RB), mean relative error (MRE) and relative root mean square error (RRMSE), as described below.

\[
R^2 = \frac{\sum^n_{i=1}(Y_{oi} - Y_o)(Y_{pi} - Y_p)^2}{\sum^n_{i=1}(Y_{oi} - Y_o)^2 \sum^n_{i=1}(Y_{pi} - Y_p)^2},
\]

\[
RB = 100 \times \frac{\sum^n_{i=1}(Y_{pi} - Y_{oi})}{\sum^n_{i=1}Y_{oi}}
\]

\[
MRE = 100 \times \frac{1}{n} \sum^n_{i=1} \left| \frac{Y_{pi} - Y_{oi}}{Y_{oi}} \right|
\]

where \(Y_{oi}\) and \(Y_{pi}\) are the observed and predicted maize yield for the year \(i\), respectively; \(Y_o\) and \(Y_p\) are the long-term mean values of observed and predicted maize yields for the period 1981–2010, respectively; \(n\) denotes the number of years. Higher values of \(R^2\) and lower RB, MRE and RRMSE indicate better model performance in reproducing the observations.

2.4. Analysis

We conduct our analysis at the country scale, because observed yields from FAO census data are only available at this scale. Therefore, gridded yields simulated by the six process crop models are aggregated for each country, with weights based on the MIRCA2000 harvest area map (Portmann et al. 2010). Here, we focus our analysis on the top ten producing countries, which are determined based on their average maize productions during the study period. Similar to process model simulations, a baseline simulation driven with observed climate and 25 sensitivity experiments under various temperature (\(-1^\circ C, 0^\circ C, +1^\circ C\), \(+2^\circ C, +3^\circ C\)) and precipitation change scenarios (\(-20\%, -10\%, 0\%, +10\%, +20\%) are conducted for the statistical and LSTM models. Comparing the simulated yields between the baseline and sensitivity experiments can quantify the separate and combined effects of temperature and precipitation. For example, the simulated yield difference between the baseline experiment and \(+1^\circ C\) warming scenario with fixed precipitation level can be used for disentangling the individual effects of temperature, while \(+1^\circ C\) warming plus 10% increase in precipitation are designed to evaluate the combined effects of warming and wetting climates. Given that the same climate scenarios are used as inputs for both machine learning, statistical and process crop models, reasonable inter-comparisons between the models can be achieved. The revealed ranges in simulated yield changes between the three types of model can therefore be used to quantify the uncertainty of climate impact assessment that arises from crop models.

3. Results and discussions

3.1. Performances of regression, LSTM and process crop models

Before using crop models to quantify climate impacts on crop yield, we have to evaluate the model performances to understand their capability to reproduce historical yield patterns. Figure 1(a) shows the boxplots of \(R^2\) based on 100 model simulations by the regression and LSTM models, and six process crop model simulations. It is shown that the regression and LSTM models both exhibit a median of \(R^2\) value greater than 0.7 for the globe, implying that our
The performances of polynomial regression (red), LSTM (black) and process-based models (blue) in simulating maize yields for the globe. The simulated yields are compared with FAO census yield, based on which the coefficient of determination ($R^2$), relative bias (RB), mean relative error (MRE) and relative root mean square error (RRMSE) are calculated. The central mark of the boxplot indicates the median, while the bottom and top edges indicate the 25th and 75th percentiles, respectively.

Statistical and LSTM models conditioned on the year term and two climatic predictors can explain most observed yield variations, despite the fact that other important factors, including vapor pressure deficit and extreme weathers, are not explicitly accounted for in the models. However, considerable sampling uncertainties exist as indicated by the wide range of $R^2$ values based on 100 samples, and a low $R^2$ of 0.3 is observed for some model iterations. Similar findings are obtained when examining the metrics of RB, MRE and RRMSE (figures 1(b)–(d)), indicating that both models can reproduce well the observed long-term mean yields. As for process crop models, the ensemble median can explain 41% of observed yield variability for the globe, but overestimate the absolute yield values, partly due to the fact that some models simulate potential yields (e.g. LPJ-GUESS and LPJmL). The performances of process models revealed in our study are broadly consistent with previous findings (Müller et al 2017, Franke et al 2020).

Regionally, a large discrepancy in model performance is found among the top ten producing countries, suggesting diverse climate impacts on maize yield across regions (supplementary figures S1–S4 available online at stacks.iop.org/ERL/17/044036/mmedia). It is shown that over 60% of yield variability can be explained by the regression and LSTM models for most countries (supplementary figure S1). Given that nonlinear climate effects are accounted for in LSTM (Malhotra et al 2015), the difference between polynomial regression and LSTM model performances indicates the important role of nonlinear climate impacts on maize yield (Schlenker and Roberts 2009, Lobell et al 2011a). As for process models, the best performance is found in USA, China and France, with a median $R^2$ of 0.42, 0.44, and 0.60, respectively. The worst performance of process models is found in Indonesia, where nonsignificant correlation with observations is found, which confirms the results by Franke et al (2020). Overall, process-based models exhibit larger biases than the regression and LSTM for most countries (supplementary figures S2–S4).

3.2. The separate effects of temperature and precipitation changes on maize yield

Figure 2 shows the separate effects of temperature and precipitation on global maize yield based on regression, LSTM and process-based models. For the globe as a whole, maize yield is shown to decrease by 6.88% for 1 °C warming, when precipitation is fixed at the baseline level. The negative temperature impacts tend to increase linearly with temperature rise in the regression model, which is broadly in line with previous studies using a similar statistical modeling approach (Lobell and Field 2007, Matiu et al 2017). Likewise, the ensemble mean of six
process-based models exhibits an approximately linear temperature–yield relationship, with 5.61% yield losses under temperature \( T + 1 \) °C. In contrast to the benefits of declining temperature in regression and process models, LSTM exhibits a non-evident yield response to the scenario of temperature \( T - 1 \) °C. When controlling temperature effects, increases in precipitation alone tend to boost yield growth, which are all captured by the polynomial regression, LSTM and process-based models. However, the regression model tends to show a flatter response of yield to precipitation changes, with the response magnitude much lower than LSTM and process models. For example, with temperature fixed at the baseline level, a 10% increase in precipitation could enhance global maize yield by 0.23%, 1.43% and 3.09% in the regression model, LSTM and process-based models, respectively. Interestingly, a 20% decrease in precipitation could cause a yield loss of 8.10% by the ensemble mean of process models, the magnitude of which is much larger than the yield gain of 5.63% by 20% precipitation increase. This suggests that droughts tend to have larger effects than heavy rains on global maize yield in process models, though large model spread is observed due to their diverse representation of plant physiological and soil processes (Elliott et al. 2015, Müller et al. 2017, Franke et al. 2020).

Regionally, negative impacts of rising temperature are obtained for most of the top ten producing countries, though the magnitudes of yield changes vary substantially (figure 3). For example, polynomial regression predicts a yield decrease of 4.09% for 1 °C warming in USA, while the largest impacts are found in Argentina (12.11%) and South Africa (13.01%), probably due to the high baseline temperature in low latitudes (Agnolucci et al. 2020). Similar to the global scale results, an approximately linear temperature–yield relationship is simulated by process-based models in China, Argentina, India and Indonesia, while an obvious nonlinearity is shown in USA, France, South Africa and Canada. Diverse regional yield responses to temperature changes are also predicted by LSTM, with nonlinear yield response to temperature rise simulated in most countries. The revealed regional differences in yield response to warming is broadly consistent with previous studies, showing the largest impacts in tropical regions compared to elsewhere (Lobell et al. 2011b). However, large uncertainty exists for county-level assessment of temperature impacts on yield, as indicated by the substantial differences between the three types of crop models. Such uncertainty tends to become larger under higher warming scenarios. In South Africa, Argentina and China, the estimates by empirical models (i.e. polynomial regression and LSTM) tend to fall outside the range of process models. In some cases, the three types of models even disagree in the change direction of yield with warming. For example, in Canada, where temperature climatology is below the optimal for maize growth, both statistical and machine learning crop models estimate a positive effect of warming, confirming the findings by Agnolucci et al. (2020) and Franke et al. (2020), while a negative temperature effect is obtained by process models.

As for precipitation, positive effects of increasing precipitation are shown across all top ten producing countries for polynomial regression, LSTM
and process-based models, with magnitudes of yield change depending on the region of interest (figure 4). The largest benefits of increasing precipitation are found in South Africa, where a 10% increase in precipitation leads to a yield growth of 4.21%, 4.80% and 11.01% by polynomial regression, LSTM and process-based models, respectively. As for the negative effects of a 10% decrease in precipitation, the largest yield reduction of $-10.86\% \sim -4.21\%$ is also simulated in South Africa by the three types of crop models. This confirms the highest vulnerability of crop production to climate variability in
South Africa (Challinor et al. 2007), where rainfed agriculture is dominant. In contrast, maize yield sensitivity to precipitation is relatively smaller in USA, China and India, probably due to the extensive application of irrigation which could well buffer precipitation effects (Vogel et al. 2019, Wang et al. 2021). In contrast to temperature predictions, both statistical and machine learning models generally fall within the range of process models in most countries. This suggests more robustness for predicting the impacts of precipitation change than temperature effects at the regional level, though substantial uncertainty remains, especially for high precipitation change scenarios.
3.3. The combined effects of temperature and precipitation on maize yield

Figure 5 shows the simulated yield changes in response to 16 combinations of temperature and precipitation change scenarios for the globe and top ten producing countries. It is found that the negative temperature impacts on yield are largely dependent on the concurrent precipitation change levels, with warming effects being partially offset by increased rainfall. Such compounding effects of precipitation are largest in the regression model, followed by process models and the machine learning model. Specifically, based on polynomial regression, the 1 °C warming-induced global yield loss could be mitigated by 3.98% with an additional 10% increase in precipitation. This suggests that a considerable portion of warming-induced yield losses is contributed by the intensified water stress, and concurrent changes in precipitation (as a proxy of surface moisture) can therefore greatly modulate yield response to temperature. With a 20% rise in precipitation, the 1 °C warming-induced yield loss could even be totally offset, pointing to the important confounding effects of precipitation in regulating warming impacts on yield. Compared to the regression model, process-based models show a smaller magnitude of confounding effects of precipitation in modulating temperature–yield relations. For example, a 10% increase in precipitation could reduce yield loss by 3.10%, while the 1 °C warming-induced yield loss could be completely offset by a 20% increase in precipitation. Without prior assumptions of yield–climate relations,
the LSTM predicted a reduction of yield loss of 1.05% and 2.63% when precipitation increases by 10% and 20%, respectively.

Regionally, the intensification of precipitation leads to an overall reduction of warming-induced yield loss for all the top ten countries, while enhanced yield loss is found with a decrease in precipitation. Specifically, as predicted by the regression model, a 10% increase in precipitation shows the largest benefit in South Africa, where a 1 °C warming-induced yield loss is mitigated by 10.01%. Similar findings are obtained for process-based models, with the largest reduction of yield loss in South Africa, where a 10% increase in precipitation can completely offset the yield loss induced by T + 1 °C. Compared to statistical and process models, the LSTM shows the smallest benefit of increasing precipitation, with yield loss offset by 6.16% under a 10% increase in precipitation. Overall, these results imply an important role of precipitation in regulating yield response to temperature changes.

3.4. Uncertainty in climate impact assessment arising from crop models

Crop models are valuable tools for assessing and predicting climate impacts on crop yields, but often show large uncertainties. Here, we show a large model spread in the estimated effects of temperature and precipitation on yield among the six process-based models (figure 2). Such uncertainty becomes more evident under extreme warming and drier scenarios, indicating greater challenges for predicting future yield changes with increasing extreme climates. For example, with precipitation fixed at the baseline level, process models show an uncertainty up to 14.64% for simulating yield changes under the T + 3 °C scenario, which more than triple that under the T + 1 °C scenario (4.52%). Likewise, by controlling temperature, yield responses to −20%, −10%, +10% and +20% of precipitation change are associated with an uncertainty up to 16.74%, 7.93%, 6.98% and 13.05%, respectively. Notably, larger uncertainties are identified under P-20% (−8.10%~−0.46%) than P + 20% (0.46%~5.63%) and P-10% (−3.69%~0.23%) than P + 10% (0.23%~3.09%), suggesting that impact assessments using process crop models are more uncertain under droughts than excessive rainfall. This has great implications for future yield projections, given that more droughts are expected under global warming (Dai 2011, 2012, Lobell et al 2014). Overall, polynomial regression and LSTM generally fall within the ranges of six process-based models for global-scale assessment. Such consistency between different types of crop models demonstrates the robustness of multi-model based climate impact assessment on global crop yield. Specifically, the uncertainty range of warming impact between the three types of models on global yield is up to −6.88%~−4.86%, −13.76%~−11.48%, −21.14%~−17.09% under T + 1 °C, T + 2 °C and T + 3 °C (supplementary table S1), respectively, while a larger range is found for the cooling effects under T−1 °C (0.10%~6.88%). As for precipitation effects, a range of −8.10%~−0.46%, −3.69%~0.23%, 0.23%~3.09% and 0.46%~5.63% under P−20%, P−10%, P + 10% and P + 20%, respectively, indicating that uncertainty is larger under drier conditions than wet conditions.

Regionally, a diverse response pattern is found for the top ten maize producing countries, with larger temperature impacts simulated in several countries. In some cases, the predictions by polynomial regression and LSTM are outside of the range of the six process models (figures 3 and 4), implying that the choice of crop model type has a large influence on the predicted impacts of climate change on yields. For example, in Argentina, polynomial regression simulated a yield loss of 36.34% under the T + 3 °C scenario, outside the range of 3.24%~26.82% by process-based models. By controlling precipitation in South Africa, a yield loss of 20.83% is estimated by LSTM under the T + 1 °C scenario, which is also outside of the range of −11.79%~0.64% by process-based models. The results suggest more pronounced uncertainties at the country level, which depends not only on the region but also on the specific climate scenarios of interest. With the South African temperature fixed at the baseline level, process models exhibit an uncertainty of up to 56.43% under the P + 20% scenario, compared to that of 40.33% under the P−20% scenario. This implies that, in contrast to global-scale findings, country-scale assessments could be associated with larger uncertainties under excessive rainfall conditions than droughts.

Further analysis shows that the confounding effects between temperature and precipitation could exert substantial influence on the uncertainty of their impacts on yield (figure 5). With rising temperature, yield change under droughts becomes more uncertain than under excessive rainfall in several countries. Taking South Africa as an example, when temperature increases from T−1 °C to T + 3 °C, the uncertainty of yield changes tends to become larger from P + 20% scenario to the P−20% scenario. This suggests that warming contributes substantially to the uncertainty of yield impact assessments under drought. Under high temperatures, a similar spread of process-based models is found across various precipitation scenarios in several countries. For example, in France, a model spread of 19% is shown under the T + 3 °C scenario, which is slightly influenced by the concurrent precipitation changes. This indicates that temperature is the major factor dominating the uncertainties of yield impact assessment in process-based models.
4. Limitations of this study

Reconciling empirical evidence and model simulations could greatly improve our ability to predict the impacts of climate change on global crop production. Our study contributes to the community by using various types of crop models for disentangling the separate and confounding effects of temperature and precipitation on global maize yield. However, there are some limitations in our multi-method study, which should be acknowledged in order to better interpret the results.

First, we analyze climate impact on crop yield at the country and global scale, which can mask local climate effects. The large-scale assessment is made mainly because the only publicly available worldwide and long-term census data on crop yield is from the FAO, and only country-scale census yield data is reported by FAO. To account for the effects of spatial heterogeneity, weights are assigned to each grid cell according to its harvest area, based on which spatial aggregation of climate indicators is performed for developing statistical and machine learning models (see methods section). We note that such a way of developing empirical models has been successfully adopted by many global investigations. Indeed, studies focusing on climate impact on crop yield at the global scale often use nationally aggregated yield data and climate indicators (e.g. Agnolucci et al 2020, Lesk et al 2016, Lobell et al 2011b, Varma and Bebber 2019, Waldhoff et al 2020), due to the lack of publicly available high-resolution of yield data across the globe. Though such large-scale investigations can mask localized climate effects, they provide valuable insights into the climate impact on yields at the national scale.

Second, crops are influenced by various other factors besides temperature and precipitation, such as vapor pressure deficit (Ray et al 2002) and CO$_2$ (Leakey et al 2009). Agricultural management practices such as multiple cropping (Seifert and Lobell 2015), irrigation (Wang et al 2021), soil mulching (Qin et al 2015) and conservation tillage (Karlen et al 2013), could further complicate the prediction of yield under climate change. Instead of including as many influencing factors as possible to accurately predict yield values, we focus on the separate and compounding effects of two major climate factors (i.e. temperature and precipitation) for two reasons: (a) they are recognized as the major climatic determinant of yield variability; (b) the examined scenarios of temperature and precipitation are available from the community-driven process modeling efforts coordinated by AgMIP, which is the prerequisite for our inter-comparison study between process-based, statistical and machine learning models.

Third, the effects of changing intra-seasonal climate variabilities are not explicitly considered. Indeed, wet and cold weather can limit the leaf size and reduce the photosynthetic capacity in the early growth stages of maize, while in the later stages, heatwave and drought could reduce the number of silks, causes poor pollination of ovules and reduce the number and size of developing kernels (Ritchie et al 1993). Daryanto et al (2016) show that maize is more sensitive to drought during reproductive than vegetative stages, while excessive rainfall would cause more maize yield losses during vegetative than reproductive stages (Li et al 2019). However, unfortunately, the climate scenarios designed by AgMIP only considers the changes in growing season mean values (Franke et al 2020). That is, crops experience the same level of changes in temperature and precipitation throughout the growing season. In order to compare with process models, we run our statistical and machine learning models using the same climate scenarios, which inhibits further investigation of the effects of intra-seasonal climate variability.

Due to the above limitations, we emphasize that our study cannot provide an accurate prediction of yield values across the world. Rather, we aim to reveal the uncertainties of climate impact assessment with a focus on the separate and compounding effects of temperature and precipitation on global maize yield. The major contributions of our study regard the use of and the inter-comparison of the predictions under various climate scenarios by process-based, statistical and machine learning crop models driven with the same input information. Such a multi-method study can provide insights to policy makers and the academic community, through revealing the similar and different behaviors of crop models.

5. Conclusions

The impacts of temperature and precipitation on maize yield are well recognized in the literature, but their global separate and confounding effects are not well quantified using multiple types of crop models. This study aims to disentangle the separate and confounding effects of temperature and precipitation on global maize yield using machine learning, statistical and process crop models. A total of 25 combinations of temperature–precipitation change scenarios are designed and fed into crop models with a consistent approach, which advances previous studies by allowing reasonable comparisons between different types of crop models.

Results show that warming by 1°C would cause a global maize yield loss of 6.88%, 4.86% or 5.61% using polynomial regression, LSTM and process-based models, respectively, and such negative temperature effects could be mitigated by 3.98%, 1.05% or 3.10% with a 10% precipitation increase. In general, larger yield loss is obtained under extreme warming scenarios, and precipitation tends to exert a larger modulating influence under low temperatures. Further results indicate that the choice of crop models would lead to large uncertainties for
climate impact assessment at the global and national scales. Overall, the three types of model show larger discrepancy in predicting temperature impacts than precipitation effects. Globally, climate impact assessment is more uncertain under drier conditions than wet conditions. Regionally, a diverse uncertainty pattern is found for the top ten maize producing countries. For example, the range of 1 °C warming impact between the three types of models is estimated to be $-5.45\%$ to $-4.09\%$, $-6.74\%$ to $-1.44\%$, and $-4.82\%$ to $-3.05\%$. $-6.52\%$ to $-1.69\%$, $-14.19\%$ to $-6.73\%$, $-10.40\%$ to $-5.88\%$, $-8.36\%$ to $-3.55\%$, $-4.80%$ to $-0.63\%$, $-20.83\%$ to $5.88\%$ and $-4.33\%$ to $-4.85\%$ in USA, China, Brazil, Mexico, Argentina, India, Indonesia, France, South Africa and Canada, respectively, and such uncertainty could even double under the 3 °C warming scenario in most countries. In addition, warming tends to enhance the divergence between the three types of models under drought conditions in most countries, demonstrating the substantial role of climate interactions in contributing to the uncertainty of yield predictions.

The results have great implications for projecting future yield changes given the increasing probability of high temperature and droughts under future warming. Through our comprehensive multi-method inter-comparisons, we emphasize the importance of using both machine learning, statistical and process crop models for climate impact assessments of crop yield, which has the added benefit of providing a more realistic estimate of uncertainty than would be provided by a single type of model.

Data availability statement

The data that support the findings of this study are openly available. Census data on annual maize yields of the globe and top ten producing countries are obtained from the Food and Agriculture Organization of the United Nations (FAO) FAOSTAT database (www.fao.org/faostat/en/#data/QC). Gridded climate data is downloaded from https://data.giss.nasa.gov/impacts/agmipc/agmerral/. The simulated yields by process models are from Global Gridded Crop Model Intercomparisons (GGCMI) project at https://agmip.org/aggrid-ggcmi/. The crop calendar map is from https://isage.nelson.wisc.edu/data-and-models/datasets/crop-calendar-dataset/. The crop harvest area map is from www.uni-frankfurt.de/45218023/MIRCA.

The data that support the findings of this study are available upon reasonable request from the authors.

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