Differences, or lack thereof, in wheat and maize yields under three low-warming scenarios

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Abstract
The availability of climate model experiments under three alternative scenarios stabilizing at warming targets inspired by the COP21 agreements (a 1.5 °C not exceed, a 1.5 °C with overshoot and a 2.0 °C) makes it possible to assess future expected changes in global yields for two staple crops, wheat and maize. In this study an empirical model of the relation between crop yield anomalies and temperature and precipitation changes, with or without the inclusion of CO2 fertilization effects, is used to produce ensembles of time series of yield outcomes on a yearly basis over the course of the 21st century, for each scenario. The 21st century is divided into 10 year windows starting from 2020, within which the statistical significance and the magnitude of the differences in yield changes between pairs of scenarios are assessed, thus evaluating if and when benefits of mitigations appear, and how substantial they are. Additionally, a metric of extreme heat tailored to the individual crops (number of days during the growing season above a crop-specific threshold) is used to measure exposure to harmful temperatures under the different scenarios. If CO2 effects are not included, statistically significant differences in yields of both crops appear as early as the 2030s but the magnitude of the differences remains below 3% of the historical baseline in all cases until the second part of the century. In the later decades of the 21st century, differences remain small and eventually stop being statistically significant between the two scenarios stabilizing at 1.5 °C, while differences between these two lower scenarios and the 2.0 °C scenario grow to about 4%. The inclusion of CO2 effects erases all significant benefits of mitigation for wheat, while the significance of differences is maintained for maize yields between the higher and the two lower scenarios, albeit with smaller benefits in magnitude. Changes in extremes are significant within each of the scenarios but the differences between any pair of them, even by the end of the century are only on the order of a few days per growing season, and these small changes appear limited to a few localized areas of the growing regions. These results seem to suggest that for globally averaged yields of these two grains the lower targets put forward by the Paris agreement does not change substantially the expected impacts on yields that are caused by warming temperatures under the pre-existing 2.0 °C target.

1. Introduction

Following the ratification of the COP21 agreements to pursue efforts of limiting warming well below 2.0 °C to 1.5 °C above pre-industrial temperatures, wide interest in characterizing mitigation and adaptation costs within a range of low-warming scenarios consistent with these temperature targets has been generated, and an IPCC special report on the subject is under way. Very few fully coupled model experiments exploring these targets and that can be consistently compared are available, however, since the focus on the lower
target came about well after the completion of CMIP5 experiments (Taylor et al 2012), and too early for the CMIP6 experiments (O’Neill et al 2016) to provide relevant information yet. This study takes advantage of one such set of experiments, run with the DOE/NCAR CESM1-CAM5 model (Hurrell et al 2013), producing climate output over the historical and 21st century periods under three alternative trajectories of global average temperature relevant to the Paris framework: one that stabilizes at a 1.5 °C anomaly by the end of the century never exceeding that level, one that overshoots briefly such level in the middle of the century, to then meet the target from above by century’s end, and a third that stabilizes at a 2.0 °C anomaly in the last decade of the century (Sanderson et al 2017). Making use of temperature and precipitation output from these experiments, and including or omitting the effects of CO₂ increases on plant growth, changes in future crop yields of wheat and maize at the global scale are derived on the basis of an empirical approach that was recently used in a similar study, comparing the benefits of mitigation between two well separated scenarios, RCP4.5 and RCP8.5 (Tebaldi and Lobell 2016, TL16 from now on) as part of the predecessor of this current collection of studies, BRACE (O’Neill et al 2017). Here the question becomes if also much smaller differences in global warming levels produce significantly different effects on crop yields. Similar to the previous study, the statistical significance of such effects and their relative differences can be robustly quantified by using sets of multiple initial condition ensemble members, thus taking into account the effects of internal variability besides greenhouse gas forcing in affecting the evolution of climate variables within and between the different futures. The focus will be on yearly outcomes and in particular on the average yield changes over consecutive 10 year windows, and how they differ across the three scenarios. The times at which differences become (or stop being) statistically significant, and by what magnitude, will be of particular interest. In addition, changes in exposure to extreme heat will be assessed, since work that is summarized in Aerenson et al (2018) shows significant differences in the occurrence and intensity of heat extremes among the three scenarios. Exposure of crop-growing regions to days above critical thresholds that are crop-specific and have been shown to damage plants if occurring at the time of flowering will be quantified and compared across the three scenarios, also in terms of spatial patterns, similar to the analysis in TL16.

These projected future impacts will take place in the context of continuing changes in agricultural practices and technologies, which will partially confound these impacts’ magnitude. When fitting the empirical model to observations, the use of yearly differences in yields and climate variables controls for the steady positive trend experienced over the historical period by crop yields, a trend due mostly to gradual progress in cultivars and other agricultural technologies, like the spread of irrigation. Therefore, the shocks estimated as an effect of climate change are to be interpreted as superimposed on the effects of other factors affecting the future progress of yields.

2. Methods

The empirical model adopted here relates year-to-year anomalies of temperature and percent precipitation to the year-to-year variations in crop yields at a global scale, as in Lobell and Tebaldi (2014) and TL16. Using the exact same data and period to fit the model as in TL16, a simple linear regression is fit to the observed record of these quantities over the period 1962–2014. FAO globally aggregated yield data for wheat and maize (FAO 2013 including updates) and HadCRU data (Morce et al 2012 including updates) is used, by aggregating the climate data into global averages weighted according to the geographical pattern of the two crop-growing regions (based on Leff et al 2004), and over a critical period of the growing season defined as a function of the location-specific date of harvest, which is obtained from the SAGE maps (Sacks et al 2010). These periods are defined differently for maize and wheat, and are chosen to represent the most weather-sensitive portions of the crop growing season. For maize, the temperature and precipitation were averaged for the period three to two months prior to harvest (e.g. June–July for a cell with a September harvest); for wheat, temperature and precipitation were averaged for the three-month period ending at harvest (e.g. February–April for a cell with an April harvest). We use a simple linear relationship between yield and temperature and precipitation rather than nonlinear models typically used in studies based on data at country or sub-country levels (e.g. Schlenker and Roberts 2009, Lobell et al 2011). These latter studies typically include observations spanning a wide range of temperatures over which crops exhibit a nonlinear response, with optimal yields at intermediate temperatures. However, global aggregates of temperature and precipitation span a much narrower range than aggregates at smaller spatial scales, and over the narrower range the relationship between yields and weather is well approximated by a linear function (Lobell et al 2011). Similarly, using growing season averages results in a much more linear response than seen when looking at the wide range of hourly temperatures experienced during a season (Schlenker and Roberts 2009). The linear response to warming is also evident in the global aggregate of yields simulated by crop simulations models, which possess nonlinear responses over large ranges of temperature but roughly linear responses to incremental warming at the global scale, at least up to a few degrees (Rosenzweig et al 2014, Asseng et al 2015). Note also that since we are fitting a statistical relation to global scale data we do not need to
account for time-invariant omitted variables that affect production at different locations, such as soil quality or national policy, and therefore our model does not need to involve fixed effects like many other empirical studies at the national or other regional scale do.

The estimated regression coefficients, which are the same as those used in TL16, indicate a sensitivity to temperature change of wheat yields of −6% (standard deviation of 1.2%) of the historical baseline (chosen as the last 20 years available, 1995–2014) for each degree of temperature warming, and a −1% (standard deviation of 0.7%) for each increase of 10% in average precipitation, consistently with other studies of the impact of warming temperatures on wheat production (Asseng et al. 2015). The maize yield regression coefficients are −7% and +1.5% respectively (with standard deviations of 1.5% and 1%). Note that both coefficients for precipitation changes are not statistically significant, in part due to the inclusion of production from irrigated areas in the FAO global statistics, and in part due to the small variations in the historical record of the globally aggregated precipitation amounts for both crops, which do not span a large enough range to elicit a clear yield response.

The linear regression coefficients are used to project impacts of temperature and precipitation changes by computing the same aggregated quantities from monthly output of the CESM model as computed from the HadCRU data. Twelve ensemble members are used from the 1.5 °C ‘not exceed’ scenario (1.5 from now on) and 12 ensemble members from the 2.0 °C scenario (2.0), while we only have nine members for the 1.5 °C overshoot scenario (1.5OS). Each individual trajectory of temperature (or precipitation) growing season/region averages (one value per year) over the course of the 21st century is transformed into anomalies from the reference period (1995–2014) and combined with the regression coefficients to obtain a yearly value of yield change, again referenced to its historical baseline. The effects of CO₂ fertilization are included by using a multiplicative coefficient derived from interpolating results from the DSSAT4 models based on CO₂ enrichment experiments, according to table S1 in supplementary material available at stacks.iop.org/ERL/13/065001/mmedia (as in TL16, Jones et al. 2003, updated in 2012 for C4 crops). As a reference, the 2.0 scenario reaches a CO₂ atmospheric concentration of 436 ppm by 2100, while both 1.5/1.5OS scenarios only reach 375 ppm (see figure 1).

Thus, time series of annual values of maize or wheat yield changes as percentages of the historical baseline are obtained, one per ensemble member.

In order to address the uncertainty in the linear regression, 500 values of the regression coefficients are randomly sampled from normal distributions with mean and standard deviations according to the point estimates listed above (according to the standard theory of linear regression with normally distributed errors), thus enlarging the number of outcomes per ensemble member by the same number. Average results across both ensemble members and coefficient samples are presented, together with uncertainty bounds obtained by the combination of the two sources. Once the three ensembles of trajectories for each crop and with or without CO₂ effects are obtained, the statistical significance of the average difference in yields between each pair of scenarios (i.e. comparing 1.5 to 2.0, 1.5 to 1.5OS, and 1.5OS to 2.0) can be tested for each of the eight ten-year windows, and the magnitude of their difference is evaluated when the test rejects the null hypothesis. For the second part of the analysis, as in TL16, bias corrected daily maximum temperature output (McGinnis et al. 2015) is used to compute the occurrence of days exceeding 34 °C for wheat and 35 °C for maize during the growing seasons as previously defined. The number of occurrence of these heat extremes is analyzed over three windows of twenty years at short-term (2021–2040) mid-century (2041–2060) and century-end (2081–2100), computing changes in occurrence within the scenarios compared to the 1995–2014 baseline period, and across the scenarios. For this analysis, only land areas with at least 2% of the area cultivated with the crop of interest are considered (based on Sacks et al. 2010).

3. Results

3.1. Changes in average yields between scenarios and their significance

Figure 2 shows the behavior of temperature and yields under the three scenarios, over time. Since precipitation does not contribute to the explanatory power of the regression model its corresponding trajectories are not shown.

Obviously, under all three scenarios, average temperatures in the growing region/season for the two crops are rising, in the context of year to year
Figure 2. Left panels: time series of CESM simulated temperature averaged over the crop’s growing season and region (the latter according to weights proportional to the fraction of grid cell cultivated); values are anomalies with respect to the 1995–2014 average. Center and right panels: time series of estimated percent changes from the 1995–2014 average yield for each of the crops, without including CO₂ fertilization effects and including them. In each panel three set of experiments are shown: twelve member ensembles for 1.5 and 2.0 scenarios and nine member ensembles for 1.5OS. Thick lines are ensemble means, shaded envelopes bound the ensemble ranges.
variability affecting both the ensemble mean (thick lines) and, in larger measure, the individual ensemble members (thinner lines). The behavior of temperature follows closely that of global warming under the individual scenarios (shown in figure S1) a well documented characteristics of future temperature projections (Tebaldi and Arblaster 2014) rising gradually in the first decades of the 21st century and stabilizing in the second part of the century for 1.5 and 2.0; peaking in the middle of the century, then decreasing, for the overshoot, 1.5OS. Note that the 1.5 not exceed concentration under the 2.0 scenario and during the overshoot phase of 1.5OS (figure 1) is the main reason for the compensation of the relatively warmer conditions under these two scenarios compared to the 1.5, making the trajectories of wheat yield changes under all three scenarios overlap. When contrasting the behavior of maize, the smaller response to CO$_2$ of the C4 crop is also compounded by the marginally higher (more negative) sensitivity of the crop to warmer temperatures (~7% compared to ~6% for wheat) which maintains the separation between the scenarios.

Separating the outcomes by successive ten years window allows us to identify the time when differences between any pair of scenarios start being statistically significant. As table 1 shows, significant differences appear starting from the decade of 2031–2040, but all differences remain below 3% of the historical baseline until the second part of the century. In those latter decades, the two scenarios stabilizing at 1.5 °C, with or without an overshoot, show either small differences (around 1%) around mid-century, or become indistinguishable again. Differences continue to be significant and to increase between 2.0 and the lower scenarios when not accounting for CO$_2$ effects, for both crops, reaching a separation of up to 4% in the later decades. The inclusion of CO$_2$ fertilization changes the outcome significantly for wheat, for which all scenarios become indistinguishable from each other. For maize there remain significant differences between the higher scenario and the two lower ones, but the magnitude of the difference decreases to below 3%.

In summary, small differences (below 3%) surface as statistically significant fairly early in the century, but only in the second half grow above that magnitude when comparing 2.0 to the 1.5 and 1.5OS scenarios, and only if we do not account for CO$_2$ fertilization. The inclusion of the latter erases any benefit of mitigation for wheat crops, and diminishes the differential impacts to below 3% for maize, even if maintaining a statistically significant differential between the scenarios.

### 3.2. Heat extremes

When analyzing the occurrence of hot days (above 34° or 35 °C) at the local scale we find significant increases within the scenarios over the course of the century over a number of areas within the crop growing regions (figure 3 for wheat, and figure S2 for maize, showing similar patterns and magnitude of changes. Also, see figure S3 for current climatological values of hot day occurrence). This is consistent with recent studies that have found statistically significant changes among these scenarios when analyzing metrics of heat extreme (Sanderson et al 2017, Aerenson et al 2018). For our metrics, we are witnessing the simple effect of a shifting mean climate on the tails of temperature distributions that have been bias corrected quantile by quantile. We see an addition of six to eight hot days within the growing seasons of the crops under 1.5; under 2.0, some areas see larger changes by the end of the century, between 10 and 15. The great majority of areas where the crops

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**Table 1.** For each ten-year window starting at 2020 and three sets of comparisons, the mean difference between the average yield change under the lower emission experiment and the higher emission experiments is shown, but only if a t-test resulted in a statistically significant difference at the 5% level. If differences are not significant the cells are left blank. Results are percentages of baseline period (1995–2014).

|          | Maize          | Wheat         |
|----------|----------------|---------------|
|          | 2021–2030      | 2021–2030     |
|          | 2031–2040      | 2031–2040     |
|          | 2041–2050      | 2041–2050     |
|          | 2051–2060      | 2051–2060     |
|          | 2061–2070      | 2061–2070     |
|          | 2071–2080      | 2071–2080     |
|          | 2081–2090      | 2081–2090     |
|          | 2091–2100      | 2091–2100     |
| No CO$_2$|                |               |
| 1.5–1.5OS| 1.3%           | 1.1%          |
| 1.5–2.0 | 1.6%           | 1.8%          |
| 1.5OS–2.0| 0.9%           | 0.7%          |
| With CO$_2$|              |               |
| 1.5–1.5OS| 1.1%           | 1.1%          |
| 1.5–2.0 | 1.2%           | 1.6%          |
| 1.5OS–2.0| 1.3%           | 1.5%          |
| 1.5–2.0 | 1.6%           | 1.5%          |
| 1.5OS–2.0| 1.3%           | 1.6%          |
are grown see significant changes under all scenarios and starting from the closest time horizon analyzed, 2021–2040.

A subset of these areas, more limited in size particularly when considering maize growing regions, see significant differences between 1.5 and 2.0, particularly by the end of the century, even if some small areas start to show small differentials that are statistically significant even by mid-century (figure 4, and S4 and S5 for a comparison of the other pairs of scenarios). By the end of the century some isolated points on the maps show benefits of six hot days or more avoided, while the majority of the areas with significant benefits from mitigation save between 1 and 5 days. Results are similar when comparing 1.5OS and 2.0 at the end of the century while the two lower pairs of scenarios show equivalent changes by that time.

4. Discussion and conclusions

This study took advantage of the only set of experiments available, to our knowledge, from a global coupled climate model simulating scenarios according to the Paris warming targets, two stabilizing at 1.5 °C, warming by 2100 with or without overshooting the target during the century, one stabilizing at 2.0 °C. We used temperature and precipitation output as predictors in an established empirical model relating global average yield changes for maize and wheat to yearly climate anomalies, over the growing region and season specific to each crop. The two crops are expected to decrease in yield because of warmer temperatures, on average, and this analysis sought to identify the time of emergence of significant differences across the three scenarios, and the magnitude of such differences, along the 21st century.

Statistical significance is assessed with respect to internal variability thanks to the availability of initial condition ensembles for all three scenarios, and with respect to the uncertainty in the statistical relation between climate variables (temperature, mainly) and yields by resampling the values of the coefficients of the empirical model according to their estimated variance.

Statistically significant differences are found, albeit small (i.e. on the order of 1 or 2% of the historical average yields). They surface even before the mid-century mark, but only in the second part of the century differences reach 3 or 4% of the 1995–2014 baseline, between the 2.0 °C scenario and the 1.5 °C scenarios. Starting from about 2060 there are no differences in the outcomes of the two lower scenarios (i.e. overshooting the target does not cause lasting consequences). This is true for both crops if the effects
of CO₂ fertilization are not included. When they are, crop yields for wheat become indistinguishable across the three scenarios, all along the 21st century, due to a compensating effect between warmer temperatures driving productivity down and enhanced CO₂ concentration in the atmosphere increasing productivity. Therefore, no benefits of mitigation can be detected between the higher and lower targets for wheat. For maize, due to lesser reactivity of plant production to the presence of increased CO₂, significant differentials in crop yield changes are maintained along the second part of the century, but of less than 3%.

As in previous work, we also analyze exposure to heat extremes, i.e. days when maximum temperature exceeds 34 °C for wheat and 35 °C for maize during the critical period that we defined as growing season. Significant increases manifest themselves early over large portions of the cultivated areas, for all scenarios. Even if, for most of the regions, changes are below ten days per season, some isolated ‘hot spots’ see larger changes, even of 15−20 days by the end of the century. When we assess the differences in these changes across scenarios, the areas where significant benefits of mitigation can be assessed become much sparser, especially for maize growing region, and mostly confined to the end of the century when comparing 2.0 to the lower scenarios. Differentials between scenarios are less than 5 days, almost everywhere.

Our empirical model has been applied, identically or based on slightly shorter records, in several earlier studies, but it is also consistent with the findings from crop modeling experiments and the broader agronomic literature, which also detect a linear response to temperature of yields aggregated at the global scale (Asseng et al. 2015). The global level of aggregation and the growing season average response are crucial in justifying the simple linear regression approach, in contrast to the need of including fixed effects, quadratic terms or other nonlinear specifications when fitting a relation at country or finer scales, and when trying to model the response of crops at more resolved time scales (e.g. daily or monthly, see Lobell et al. 2011 and references therein). Also, projections made with crop simulation models tend to show linear responses at the global aggregate level for warming up to 3 °C (Rosenzweig et al. 2014), and recent work has shown that below this level of warming the responses of statistical models using globally aggregated data agree well with responses from either statistical models using finer level data or simulation models (Zhao et al. 2017).
As in previous work, these findings have the caveat that empirical analysis, while controlling for steady but gradual progress, cannot foresee step changes in agricultural practices that would make current vulnerabilities inconsequential. We also cannot account for other disturbances like pest outbreaks, which neither our empirical model, nor process-based models, fully represent and whose intensity and frequency of occurrence may be exacerbated by climatic changes. The other potentially critical effect that our study does not include is the response of crops to heat extremes, whose occurrence we have shown is changing towards higher frequencies, but whose effect on yields are not quantified. Recent work has shown the detrimental effect of extreme heat and droughts on crops (Lesk et al 2016, Zampieri et al 2017), with year to year fluctuations in global production being significantly correlated to extremes, through their effects on national production. The effects of hot days as defined in this study is highly dependent on their occurrence at critical reproductive stages during individual plants development, and can lead to failure, but empirical data is not available on the basis of which to fit a robust statistical model that would quantify expected production losses across the world.

It is possible that other crops would be more sensitive to differences in the emissions scenarios than the two crops considered in this study. However, we note that wheat and maize are two of the most sensitive crops to warming, given their physiology and current growing environments, with previous work finding these crops more affected by recent climate changes than other crops such as rice or soybean (Porter et al 2014, Lobell et al 2011).

As in the previous BRACE studies, these results have been obtained on the basis of a single model, NCAR/DOE CESM, and therefore our analysis cannot address uncertainties related to model structural choices. For the current application, this type of uncertainties would not translate in the level of warming, with year to year fluctuations in global production being significantly correlated to extremes, through their effects on national production. The effects of hot days as defined in this study is highly dependent on their occurrence at critical reproductive stages during individual plants development, and can lead to failure, but empirical data is not available on the basis of which to fit a robust statistical model that would quantify expected production losses across the world.

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As in the previous BRACE studies, these results have been obtained on the basis of a single model, NCAR/DOE CESM, and therefore our analysis cannot address uncertainties related to model structural choices. For the current application, this type of uncertainties would not translate in the level of warming, since that is set by design in order for these scenarios to reach the specific warming targets. However, the amount of CO₂ in the atmosphere consistent with these targets is model specific, and a model, say, with a higher climate sensitivity than CESM would reach the same targets with a lower concentration of CO₂ in the atmosphere, affecting the evaluation of the CO₂ fertilization effects. A different magnitude of year-to-year variability, another quantity that is model-specific, also would affect results for both parts of the study. As in the BRACE studies, we offer this analysis as a first evaluation of the differential effects of these scenarios, and when CMIP6 results become available the community will be in the position of re-evaluating similar impacts in a multi-model framework.

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