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A statistical analysis of three ensembles of crop model responses to temperature and CO_2 concentration

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Dr. Nadine Brisson passed away in 2011 while this work was being carried out.

Abstract

Ensembles of process-based crop models are increasingly used to simulate crop growth for scenarios of temperature and/or precipitation changes corresponding to different projections of atmospheric CO_2 concentrations. This approach generates large datasets with thousands of simulated crop yield data. Such datasets potentially provide new information but it is difficult to summarize them in a useful way due to their structural complexities. An associated issue is that it is not straightforward to compare crops and to interpolate the results to alternative climate scenarios not initially included in the simulation protocols. Here we demonstrate that statistical models based on random-coefficient regressions are able to emulate ensembles of process-based crop models. An important advantage of the proposed statistical models is that they can interpolate between temperature levels and between CO_2 concentration levels, and can thus be used to calculate temperature and [CO_2] thresholds leading to yield loss or yield gain, without re-running the original complex crop models. Our approach is illustrated with three yield datasets simulated by 19 maize models, 26 wheat models, and 13 rice models. Several statistical models are fitted to these datasets, and are then used to analyze the variability of the yield response to [CO_2] and temperature. Based on our results, we show that, for wheat, a [CO_2] increase is likely to outweigh the negative effect of a temperature increase of +2°C in the considered sites. Compared to wheat, required levels of [CO_2] increase are much higher for maize, and intermediate for rice. For all crops, uncertainties in simulating climate change impacts increase more with temperature than with elevated [CO_2].

Key-words: climate change, crop model, emulator, meta-model, statistical model, yield

1. Introduction

Many studies have been carried out in recent decades to assess the effects of climate change on crop yield and other key crop characteristics. In these studies, one or several crop models were used to simulate crop growth and development for different projections of atmospheric CO_2 concentration, temperature and precipitation changes (Semenov et al., 1996; Tubiello and Ewert, 2002; White et al., 2011). AgMIP, the Agricultural Model Intercomparison and Improvement Project (Rosenzweig et al., 2013), builds on these studies to explore the value of an ensemble of crop models for assessing effects of climate change scenarios for several crops in contrasting environments.

The AgMIP studies generate large datasets, including thousands of simulated crop yield data. They include series of yield values that are obtained by using standardized protocols that combine several crop models with different climate scenarios defined by several climatic variables (temperature, $CO_{2,}$ precipitation, etc.). Such datasets potentially provide new information on the possible effects of different climate change scenarios on crop yields. However, it is difficult to summarize them in a useful way due to their structural complexity; simulated yield data can differ among contrasting climate scenarios, sites, and crop models. Another issue is that it is not straightforward to interpolate the results obtained for the considered scenarios to alternative climate scenarios not considered in the initial simulation protocols. Additional crop model simulations for new climate scenarios is an option but this approach is costly, especially when a large number of crop models is used to generate the simulated data.

Statistical models have been used to analyze responses of measured yield data to climate variables in past studies (Lobell et al., 2011). They were also recently used in meta-analyses on the effect of climate change on crop yields (Wilcox and Makowski, 2014; Challinor et al., 2014). However, the use of a statistical model to analyze the variability of crop model responses to climate change factors is a rather new idea. We demonstrate herewith that statistical methods can play an important role in analyzing simulated yield datasets obtained with ensembles of process-based crop models using standardized protocols. Formal statistical analysis is helpful to estimate the effects of different climatic variables on yield, and to describe the between-model variability of these effects. Statistical methods can also be used to develop meta-models, i.e., statistical models summarizing process-based crop models. Such meta-models may enable scientists to explore more efficiently the effects of new climate change scenarios not initially included in the simulation protocol.

Our approach is illustrated with three datasets of simulated yields obtained by AgMIP for maize, wheat, and rice generated by ensembles of process-based crop models (Asseng et al., 2013; Bassu et al., 2013; Li et al., 2015). The yield datasets were used to develop a meta-model that provides a simplified representation of the original ensembles of crop models. The proposed meta-model is a statistical regression with random coefficients describing the variability of the simulated yield data across the original crop models. Once fitted to the simulated yield datasets, the meta-models were used to analyze the variability of the projected effects of climate changes among crop models, and between alternative crops. The meta-models were also used to study the effects of temperature-change and CO_2-change scenarios that were not initially tested with the original ensemble of crop models. Finally, the results obtained with the meta-model were used to compare simulated uncertainties and to assess the impact of temperature and CO_2 concentration changes on yields of maize, wheat, and rice.

2. Materials and Methods

2.1. Simulated yield data

We used the maize, wheat, and rice datasets presented by Asseng et al. (2013), Bassu et al. (2014), and Li et al. (2015). Yield data were simulated with 19 maize models, 26 wheat models, and 13 rice models. For each crop species, models were calibrated and then run for four contrasting sites located in France (Lusignan), USA (Ames), Brazil (Rio Verde), and Tanzania (Morogoro) for maize, in The Netherlands (Wageningen), Argentina (Balcarce), India (New Delhi), and Australia (Wongan Hills) for wheat, and in the Philippines (Los Baños), China (Nanjing), India (Ludhiana) and Japan (Shizukuishi) for rice.

The simulation protocols and climate scenarios are described in Rosenzweig et al. (2013), Asseng et al. (2013), Bassu et al. (2014), and Li et al. (2015). The baseline scenario corresponded to the 1980-2010 historical climates and assumed a CO_2 concentration of 360ppm (mean of 1995). The other climate scenarios were defined from the baseline weather series by changing the daily maximum and minimum temperature and CO_2 concentration For all species, four temperature changes (+0, +3, +6, +9°C) and five atmospheric CO_2 concentration changes (+0, +90, +180, +270, +360 ppm) were used. Thirty years of yield data were generated with each crop model for each scenario, and the simulated yield values were averaged over the years. The total number of mean yield data was equal to 1,764 (441 per site) for maize, to 2,592 (648 per site) for wheat, to 1,138 (282 to 286 per site) for rice. Details of the maize, wheat, and rice protocols can be found in Bassu et al. (2014), Asseng et al. (2013), and Li et al. (2015) respectively.

2.2. Statistical model

Simulated maize, wheat and rice yield data were analyzed using two-level statistical random-effect models (Davidian and Giltinan, 1995; Pinheiro and Bates, 2000) relating mean yield (averaged over 30 years) to temperature change, atmospheric CO_2 concentration change, and their interaction. The following statistical model was used to analyze yield data for each crop and each site separately:

Level 1, within crop model

$$Y_{ij} = {}_{0i} + {}_{1i}\, T_{ij} + {}_{2i}\, T_{ij}^2 + {}_{3i}\, C_{ij} + {}_{4i}\, C_{ij}^2 + {}_{5i}\, C_{ij}\, T_{ij} + {}_{ij}, \qquad (1)$$

where ${}_{ij} \sim N\left(0, {}^2\right)$ (assumed independently and identically distributed), Y_{ij} is the mean yield (averaged over 30 years) simulated with the i^th crop model, i=1, ..., P, for the j^th scenario; j=1, ..., Q_i, T_{ij}, C_{ij} are the temperature change (compared to the baseline scenario), and atmospheric CO_2 concentration change for model i and scenario j, Q_i is the number of scenarios tested with model i, ^{2} is a variance describing the residual error,

Level 2, between crop models

$${}_{ki} \sim N\left({}_{k}, {}_{k}^{2}\right), \text{ k =0, ..., 5.} \qquad (2)$$

where ${}_{ki}$, k=0, ..., 5, are six random regression coefficients distributed according to independent Gaussian probability distributions, ${}_{k}$ k=0, ..., 5, are the seven mean regression coefficient values representing the mean yield baseline (${}_{0}$), the mean effect of temperature, the mean effect of CO_2, and the mean effect of temperature-CO_2 interaction (${}_{1}$,... ${}_{5}$) over the P crop models (i.e., the expected values of ${}_{ki}$, k=0, ..., 5). The six variances, ${}_{k}^{2}$ k=0, ..., 5, describe the between-model variability of the random regression coefficients (i.e., the variances of ${}_{ki}$, k=0, ..., 5).

This statistical model assumes that the ensemble of P crop models is a sample taken within a population including all possible crop models for a given crop while flexibly allowing for the incorporation of additional crop models in the future. The probability distributions defined by Eq. (2) describe the between-crop model variability of the yield response to climate change factors within the whole population of crop models. These probability distributions cover the ranges of climate effects considered by different crop models. The relationship defined by Eq. (1) is assumed to be valid for all crop models, but its parameters $_{ki}$, k=0, ..., 5, are assumed to vary among crop models. This statistical model describes 30-year mean yield responses and is not intended to describe the year-to-year variability of crop yields. Considering year-to-year variability would require extra random terms and additional parameters and would overly complicate the calculated model. This option was thus not considered here. The statistical model could be easily extended to deal with additional variables such as rainfall or farmers' practices.

The population parameters of the statistical model $_k$, ^2_k, and ^{2} were estimated by restricted maximum likelihood. The model-specific regression coefficients $_{ki}$, k=0, ..., 5, i=1, ..., P, were estimated by Best Linear Unbiased Predictor using the R software package "nlme" (Pinheiro and Bates, 2000), and the estimated values will be henceforth referred to as $_{eki}$. The model was fitted to data for each crop and each site separately, but for all crop models together. Results were analyzed site by site.

2.3. Assessment of the statistical model

The statistical model (Eqs. 1-2) was compared to other statistical models, including models with fewer explanatory variables, models with fewer random coefficients, and a model including no random coefficient (i.e., classical linear regression). All models were compared by using the Akaïke Information Criterion (AIC, Akaïke, 1973), where a lower AIC value corresponds with a better model. The AIC was calculated using the "AIC" function of R. We found that the model defined by Eqs. (1-2) led to lower AICs than the simpler models. The AIC of classical linear regression model was very different from the value obtained with the random coefficient model (Eqs. 1-2); the values of AIC obtained with the classical linear regression model were higher by 78% to 357% depending on the crop and on the site. The assumption that the residual errors $_{ij}$ were independent was assessed by developing another statistical model that incorporated the correlated residual errors. This model was fitted using the "correlation" argument of the "lme" function of R. The AIC of this model was higher, and the estimated correlation coefficients were very close to zero (from -9.9 10^{-3} to 7.6 10^{-4}, depending on the crop and on the site). In order to check the assumption of constant residual variance, a statistical model with a non-constant residual variance was fitted to the data using the “weights” argument of the “lme” function of R. This model was not selected because its AIC was higher. The quality of fit of the statistical model (Eqs. 1-2) was also assessed using graphical analysis and by calculating the coefficient of determination (R^2). The value of R^2 was 0.99 for all crops (Fig.1). Outputs of the statistical model (Eqs. 1-2) were also compared to the original simulated yield data in Fig. 2 for three sites and three crop models per site.

2.4. Estimation of the effect of climate change on yield

The statistical model described above was used to compute three different types of outputs:

- The average yield loss/gain due to climate change over the ensemble of crop models.
- The yield gain/loss estimated for individual crop models due to changes in climate variables.
- The probability of yield loss compared to the baseline yield.

For maize, the average yield difference obtained between a given climate change scenario (characterized by T and C) and the baseline scenario was expressed as

$$Y = {}_{1}\ T + {}_{2}\ T^2 + {}_{3}\ C + {}_{4}\ C^2 + {}_{5}\ C\ T \qquad (3)$$

The yield difference described in Eq.(3) is averaged over all crop models; this difference corresponds to an average yield gain or to an average yield loss over the P crop models. Eq. (3) defines a meta-model that simulates the average output of the original ensemble of crop models. This meta-model enables the computation of the yield differences for any change in temperature and CO_2, T and C, at each of the four considered sites.

For a given crop model i, the expected yield difference was expressed as

$$Y_i = {}_{e1i}\ T + {}_{e2i}\ T^2 + {}_{e3i}\ C + {}_{e4i}\ C^2 + {}_{e5i}\ C\ T \qquad (4)$$

Eq.(4) defines a meta-model simulating the output of the ith crop model. The yield difference (4) is crop model-specific, and represents an estimation of the expected yield difference resulting from changes in temperature and CO_2 concentration change equal to T and C, calculated with the ith crop model. It corresponds to an emulation of the mean climate change effect on yield that would have been obtained with the ith crop model if this crop model was run for a climate change scenario characterized by T and C.

The statistical model defined by Eqs. (1-2) was also used to compute the probability of yield loss $\mathrm{Prob}(\ Y_i > 0)$ that results from a change in the temperature and CO_2 concentration.

This probability was computed from the following Gaussian probability distribution $N\left(\ _{Y}, \ ^{2}_{Y}\right)$ as

$$_{Y} = \ _{1}\ T + \ _{2}\ T^{2} + \ _{3}\ C + \ _{4}\ C^{2} + \ _{5}\ C\ T \tag{5}$$

$$^{2}_{Y} = \ ^{2}_{1}\ T^{2} + \ ^{2}_{2}\ T^{4} + \ ^{2}_{3}\ C^{2} + \ ^{2}_{4}\ C^{4} + \ ^{2}_{5}\ C^{2}\ T^{2} \tag{6}$$

Note that the variance defined by Eq.(6) is not constant but varies as a function of the climate-scenario characteristics. For illustration, the quantities defined by Eqs.(3-6) were calculated for values of T and of C ranging from 0 to +6°C (with a step of 0.1°C) and from 0 to +360ppm (with a step of 1ppm) respectively, i.e., T=0, 0.1, 0.2, ..., 5.9, 6°C, C =0, 1, ..., 359, 360ppm. Some of the considered values of T and of C were initially included in the simulation protocol (e.g., T=+3°C, C =+180ppm) but most of them were not (e.g., T =+2°C, T =+4°C, C =+100ppm). These calculations were done to demonstrate the capability of the meta-model to study the effects of temperature-change and CO_2-change scenarios that were not initially tested with the original ensemble of crop models.

3. Results

3.1. Yield response to increase in temperature

Fig. 3 shows the change in yield from the baseline for one maize site (Fig.3A), one wheat site (Fig.3C), and one rice site (Fig.3E) as affected by an atmospheric CO_2 concentration increase of 180ppm ([CO_2]=540ppm) and an increase of mean seasonal temperature ranging from 0°C to 6°C (Fig.3 ACE). Each emulated model yield response is calculated by using the crop model-specific coefficients $_{eki}$ (k=0, ..., 5, i=1, ..., P) and is plotted with a grey line, and thus can be seen as a substitute for a given crop model, but without the need for re-running the original, process-based crop models. Positive yield differences can be interpreted as mean yield gain and, conversely, negative yield differences can be interpreted as mean yield loss. The solid red curve indicates the mean of the emulated yield responses to the given climate scenario as compared to the baseline, i.e., the effect averaged over all crop models. The red dashed curves indicate the 10th and 90th percentiles of the climate-change effect. About 10% of the crop models predict yield effects lower/higher than the values given by the lower/upper dashed curve.

According to Fig. 3(A, C, E), most crop models estimate that a temperature increase negatively impacts yields of maize, wheat, and rice at these sites. But this effect is highly variable among crop models, with some models predicting little response to temperature. For maize, Fig. 3A illustrates how, on average across the ensemble of crop models, the statistical model emulates a yield loss when the temperature exceeds +1°C with a CO_2 concentration increase of 180ppm in Morogoro, Tanzania. In contrast, the models suggest that wheat in Wageningen (The Netherlands) and rice in Shizukuishi (Japan) would require a temperature increase of 3.6 °C and 5°C, respectively, before experiencing a yield loss. For a CO_2 concentration increase of 180ppm, the averaged emulated projections reported in Fig. 3(ACE) indicate that moderate temperature increases could lead to gains in wheat and rice productions in these two locations. However, some of the considered crop models predict a stronger negative impact of temperature for wheat and rice. The 10th percentile of the emulated wheat and rice yield response to temperature is indeed negative when the temperature increase exceeds 1.5°C (Fig. 3 ACE).

Fig. 3 also reveals the large variability among crop models and displays how this variability increases as a function of temperature. The differences between the 10th and 90th percentiles are much larger for higher temperature increases, at a given CO_2 concentration. For example, for wheat in Wageningen (The Netherlands), the difference between the 10th and 90th percentiles is lower than 2 t ha^{-1} when the temperature increase is equal to +1°C, but becomes higher than 4 t ha^{-1} when the temperature increase reaches +4°C. This result indicates that the differences among crop models and therefore the model uncertainties are much larger for high than for small temperature increases.

This result is confirmed by the probability densities $N\left(\mu_Y, \sigma^2_Y\right)$ (Eqs. 3-4) shown in Fig. 4 for each crop (maize, wheat, rice) and all sites. The distributions presented in Figure 4 describe the variability of simulated yield loss (or yield gain) values among crop models, for a temperature increase of either +2 or +4°C at a concurrent CO_2 concentration increase equal to +180ppm. In all sites, the distributions are more peaked for a temperature increase of +2°C and are flatter for a temperature increase of +4°C. This result reveals that the variability among crop models is systematically greater for a large than for a low temperature increase. The difference is particularly important for rice (Fig. 4EF). These plots also show which regions are most affected by a +2 or +4°C temperature increase, especially for rice, showing the already warm Philippines and India as the most affected sites.

3.2. Yield response to increase in CO_2 concentration

Fig. 3 shows the effect of climate change at one site for maize (Fig.3B), wheat (Fig.3D), and rice (Fig.3F) yields under increasing levels of CO_2 concentration, ranging from 0 to +360ppm from the simulated baseline concentration (i.e., 360 to 720ppm) and for a constant temperature increase of +2°C. Fig. 3B illustrates for maize how a majority of the crop models for maize in Tanzania predict a yield loss for a temperature increase of temperature increase of +2°C and the full range of considered CO_2 concentration. For maize in this site, the mean curve suggests that the benefits of an increased CO_2 concentration are small, and do not outweigh the negative effect resulting from an increase of +2°C.

The fitted response curves obtained for wheat in Wageningen (The Netherlands) and for rice in Shizukuishi (Japan) (Fig.3 DF) show a different pattern. Compared to maize in Tanzania, the effect of a CO_2 concentration increase is stronger for wheat and rice. This result was expected based on literature for crops with C-3 vs C-4 photosynthesis (Hatfield et al., 2011). The effect of CO_2 is highly variable among crop models; some models have strongly positive slopes over the range of CO_2 concentrations, whereas others show slopes close to zero. When averaged over crop models, the negative effect of the +2°C temperature increase is overcome by the positive CO_2 effect (yield gain) as soon as the CO_2 concentration increase reaches 100ppm in the two considered sites (Fig. 3DF). However, the 10^{th} percentiles are negative for all tested CO_2 concentrations for both wheat and rice, and this result reveals that more than 10% of the crop models predict a yield loss compared to the baseline, even for high CO_2 concentrations (Fig. 3DF).

Fitted rice yield response to CO_2 concentration in Shizukuishi in Japan (Fig. 3F) is similar to wheat response in Wageningen in The Netherlands (Fig. 3D). On average over crop models, the climate change effect on rice yield is positive for the whole range of tested CO_2 concentrations in Shizukuishi. As for wheat, the 10% percentiles of yield effects are negative for all tested CO_2 concentrations, and this result reveals that more than 10% of the crop models predict a yield loss compared to the baseline, even for high CO_2 concentrations (Fig. 3F). Fig. 3BDF shows that between-crop model variability tends to increase with CO_2 concentration, but this effect is much smaller than for the effect of temperature (Fig. 3ACE). The level of divergence between crop model predictions does not strongly increase in response to CO_2.

Figure 2 also illustrates the yield responses to CO_2 concentration increase, but for a limited number of models and for a temperature increase of +3°C. This confirms that the yield response to CO_2 concentration is stronger for wheat and rice than for maize.

3.3. Probability of yield loss

Fig. 5 gives a more general picture of the results. Here, the three crops (maize, wheat, rice), and two temperature changes (+2°C and +4°C) are considered for all the sites. The curves displayed in Fig. 5 show the yield loss probability $\text{Prob}(\ Y<0)$ attributed to two levels of temperature increase (+2° and +4°C) as a function of increasing increments of CO_2 concentration, ranging from 0 to +360ppm. The yield loss probability represents the proportion of crop models that predict a yield loss due to changes in temperature and CO_2 concentration for a given crop in a given site. A probability of 0.5 indicates no evidence of yield loss or yield gain.

The higher the CO_2 concentration, the lower the risk of yield loss (Fig.5). The yield loss probability curves show different patterns between crops, sites and temperature change. For maize (Fig.5AB), yield loss probabilities are almost always higher than 0.5 (with one exception in Ames (USA) for a temperature increase of +2°C, and CO_2 concentrations higher than 250ppm). For wheat (Fig.5CD), yield loss probabilities become lower than 0.5 in all sites for at least some of the considered CO_2 concentrations. In one site (Wongan Hills in Australia), these probabilities are even systematically lower than 0.5 for all tested concentration when the temperature increase is equal to +2°C (Fig.5C). These results show that, for wheat, a majority of crop models predict that an increase of CO_2 concentration can outweigh the negative effect of a temperature increase. Results obtained for rice are highly variable across sites (Fig. 5 EF). In some sites, the yield loss probability is lower than 0.5 for relatively low levels of CO_2 concentration increases, whereas the probability remains higher than 0.5 for all tested CO_2 concentrations in other sites (Los Baños in Philippines, and Ludhiana in India).

The curves presented in Fig. 5 were used to compute the thresholds of [CO_2] increase required to obtain a probability of maize, wheat, and rice yield gain higher than 0.5 (i.e., more than 50% chance of yield gain). These thresholds were computed for two values of temperature increase (+2 and +4 °C) and four sites per crop (Table 1). As expected, these thresholds are all higher than +360ppm for maize (the highest CO_2 concentration increase considered in this study) with one exception (Ames in USA with a temperature increase of +2°C). For wheat, the thresholds range from +0 to +117ppm and from +59ppm to +358ppm for a temperature increase of +2°C and +4°C respectively. The thresholds take intermediate values for rice (Table 1).

4. Discussion and conclusions

Our study shows how yields simulated by ensembles of process-based dynamic crop models can be summarized by statistical models (meta-models) that are based on random coefficient regressions. These statistical models describe the between-crop model variability of the simulated yield data using probability distributions. They can be used to compute key simulated quantities such as mean yield loss, percentiles of yield loss, and probabilities of yield loss as functions of temperature change and CO_2 concentration change. These statistical models are helpful for analyzing risk of yield loss due to climate change factors at the locations where the original simulations were conducted, but for a higher number of climate scenarios and without the need of re-running the original ensemble of process-based models.

Regression models with random parameters were previously used in a meta-analysis on the effect of climate change on crop yields (Wilcox and Makowski, 2014), where yield data were extracted from published papers, and random parameters were used to describe the between-site variability of the yield response to climate change factors. In these simulation experiments, the results varied not only due to different locations, crop management and climate data, but also due to the use and parameterization of different individual crop models (Wilcox and Makowski, 2014; Challinor et al., 2014). Contributing variability to model uncertainty and natural variability, an important distinction for using such results for decision making (Lehmann and Rillig, 2014), was not possible in the studies by Wilcox and Makowski (2014) and Challinor et al. (2014) due to the non-systematic variation in models, model parameters, sites, and climate scenarios considered. In our study, the use of standardized protocols for each model and applied across the three crops allowed a clear separation of causes of impact variability due to models, sites and climate factors. Therefore, in our study, the random parameter distributions applied do not describe the between-site variability but the variability among process-based crop models. The statistical models proposed in this study thus correspond to meta-models emulating ensembles of complex crop models.

An important advantage of our meta-models is that they handle the interpolation between temperature levels and between CO_2 concentration levels in a standardized manner. Our meta-models can thus be used to calculate temperature and [CO_2] thresholds leading to yield loss or yield gain, and these thresholds can help agricultural and climate scientists to identify the climate change scenarios that are likely to lead to yield gains and yield losses. The capabilities of the meta-models were illustrated using three yield datasets generated by the AgMIP model intercomparison studies for maize, wheat, and rice (Asseng et al., 2013; Bassu et al., 2014, Li et al., 2015). Our results show that, for wheat, climate change has a 50% chance to result in a yield gain if [CO_2] increases by at least +117ppm (depending on the site) (i.e., [CO_2]=507ppm) and if temperature concurrently increases by +2°C (Table 1). Required levels of [CO_2] increase were found to be much higher for maize, and intermediate for rice. It is important to mention that the [CO_2] thresholds for yield gain/loss are related to the baseline scenario considered for simulating yield data. The use of other baselines (characterized by different temperature regimes) may lead to different thresholds. We do not advise using the meta-models for temperature and CO_2 concentration changes beyond the intervals considered in the original protocols. These intervals are already large (from 0 to +9°C for temperature changes and from 0 to +360ppm) and there is thus little practical interest in considering more extreme temperature and [CO_2] increases. Moreover, there is no guarantee that the meta-models will perform correctly for more extreme climate scenarios

Our meta-models can be used to quantify the effects of temperature and [CO_2] on yields, their interactions, and their variability between sites and between all the considered crop models. They thus constitute powerful tools for exploring process-based crop model responses to climate factors. Results obtained here partly confirm those obtained by Wilcox and Makowski (2014) who found that the effects of high CO_2 concentrations outweighed the effects of increasing temperature (up to +2◦C), leading to increasing yields of wheat. However, the CO_2 concentration threshold leading to a yield gain is smaller in our study (from 390 to 507ppm, depending on the sites) than in Wilcox and Makowski (2014) (640 ppm in average). This difference is partly due to the fact that Wilcox and Makowski (2014) considered a higher number of sites located in many different countries whereas only four sites were considered here per crop.

Our meta-models also show that the divergence among the maize, wheat, and rice crop models (and therefore the uncertainty in the simulated results) increases as a function of temperature (the higher the temperature change, the higher the between-crop model variability) due to model uncertainties. The effect of CO_2 concentration on the variability among crop models is much smaller. This is consistent with the individual crop results reported by Asseng et al. (2013), Bassu et al. (2014), and Li et al. (2015). This however does not necessarily mean that models capture the effects of increased CO_2 better than the effects of increased temperature: rather it could indicate that models use similar approaches to simulate the effect of elevated CO_2. Therefore, caution is required when models are used for impact assessments with late century climate scenarios where temperature changes are expected to be large. Multi-model applications (Martre et al. 2015) and model improvements with field experimental data (Asseng et al. 2015) are needed to reduce model uncertainties for such assessments.

One of the main interests of the proposed statistical model lies in its ability to describe the between crop-model variability using probability distribution functions. The estimated parameter values of this statistical model are linked to the chosen ensemble of process-based crop models used to simulate the yield outputs. The use of a different set of crop models may change the fitted responses. For example, if one uses an ensemble of crop models all showing similar responses to temperature and to CO_2 concentration, the estimated variances of the random coefficients will be close to zero and the fitted yield probability distribution will be narrow and peaked. On the other hand, if the crop models included in the ensemble show contrasting responses, the estimated variances of the random coefficients will be high, and the fitted yield probability distribution will be less peaked and more flat.

The results presented in this paper are only valid for the locations and the range of climate conditions considered for fitting the statistical model. The simulated yield responses are thus site-specific. In future work, the meta-models presented here could be extended in two different ways. First, they could be applied to a dataset including simulations obtained for a larger number of sites. It may then possible to improve the meta-models by including covariables describing site characteristics (e.g., soil type, agricultural practices) in order to explain the dominant causes of the between-site variability. Second, our meta-models could be extended in order to describe the between-year variability of yields for different climate scenarios. This could be achieved by using a more complex statistical model in order to describe yearly yield values and their distributions. Simulated yearly yields are likely to be correlated across models, and more sophisticated probability distributions thus need to be considered in order to provide a realistic description of the data.

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