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The Assessment of Impacts and Risks of Climate Change on Agriculture (AIRCCA) model: a tool for the rapid global risk assessment for crop yields at a spatially explicit scale

Francisco Estrada[a], W. J. Wouter Botzen[b] and Oscar Calderon-Bustamante[c]

ABSTRACT
A main channel through which climate change is expected to affect the economy is the agricultural sector. Large spatial variability in these impacts and high levels of uncertainty in climate change projections create methodological challenges for assessing the consequences this sector could face. Crop emulators based on econometric fixed-effects models that can closely reproduce biophysical models are estimated. With these reduced form crop emulators, we develop AIRCCA, a user-friendly software for the assessment of impacts and risks of climate change on agriculture, that allows stakeholders to make a rapid global assessment of the effects of climate change on maize, wheat and rice yields. AIRCCA produces spatially explicit probabilistic impact scenarios and user-defined risk metrics for the main four Intergovernmental Panel on Climate Change's (IPCC) emissions scenarios.

KEYWORDS
agriculture, climate change, integrated assessment model, panel model

JEL Q12, Q54
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INTRODUCTION

A significant body of the literature suggests that agriculture is the economic sector that would be most affected by climate change, and that changes in agricultural productivity could significantly impact food security at the global, regional and local levels (Intergovernmental Panel on Climate Change (IPCC), 2014; Kurukulasuriya et al., 2006; Rosenzweig et al., 2014; Rosenzweig & Parry, 1994; Schmidhuber & Tubiello, 2007). Two-thirds of the caloric energy in human diets are obtained from the three major global crops: maize, wheat and rice (Cassman, 1999). Rainfed agriculture constitutes a large share of the food consumed worldwide, and more than 90% of the farmed land in Sub-Saharan Africa and Latin America and more than 60% in large parts of

CONTACT
[a] **(Corresponding author)** feporrua@atmosfera.unam.mx
Centro de Ciencias de la Atmósfera, Universidad Nacional Autónoma de México, Ciudad Universitaria, Circuito Exterior Mexico; and Institute for Environmental Studies, Vrije Universiteit, Amsterdam, the Netherlands.
[b] Institute for Environmental Studies, Vrije Universiteit, Amsterdam, the Netherlands; and Utrecht University School of Economics (USE), Utrecht University, Utrecht, the Netherlands.
[c] Centro de Ciencias de la Atmósfera, Universidad Nacional Autónoma de México, Ciudad Universitaria, Circuito Exterior, Mexico.
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Asia (Wani et al., 2009). Moreover, rainfed agriculture is closely related to food security in developing countries such as India, where 70% of the population depends on such agriculture (Ramirez-Cabral et al., 2017; Reddy & Syme, 2014). In Mexico, 59% of the rainfed agricultural land is devoted to maize, and at least 50% of this area is for self-consumption providing the main nutritional base for about 20 million people (Murray-Tortarolo et al., 2018). Observed trends in climate during the period 1980–2008 have already produced decreases of approximately 5% in maize and wheat production at the global scale, while the global rice production has remained stable because regional decreases and increases largely offset each other (Lobell et al., 2011). In some countries, climate change impacts on crop yields have been already detectable and large enough to counter positive factors such as technological improvement and CO_2 fertilization (Lobell et al., 2011; Moore & Lobell, 2015). Global wheat, maize and rice production could decrease at rates of 6.0%, 7.4% and 3.2%, respectively, per 1°C increase in global temperatures, with high spatial variability in the distribution of changes in production (Asseng et al., 2015; Peng et al., 2004; Zhao et al., 2017). Climate change could decrease global grain yields by about 17% by 2050, and even including endogenous economic responses, this reduction could be 11% (Nelson et al., 2013).

An important limitation in most studies, including large international projects such as the Agricultural Model Intercomparison and Improvement Project (AgMIP), is that estimates of future impacts are based on a single (or just a few) climate model scenario, which prevents formal risk analysis. These point estimates greatly ignore the uncertainty in climate models' projections and it is unknown if the projected impacts represent extreme or moderate cases (Estrada et al., 2012). Another common shortcoming of the assessments of climate change on agriculture is that the representation of spatial variability of impacts is often ignored, typically focusing on state, country level or broader regions. However, spatial variability of impacts can be very large. For example, although by 2055 Africa and Latin America could have small aggregated losses of approximately 10% reduction in maize production from climate change, these losses would concentrate in specific areas (Jones & Thornton, 2003). Such concentrations are especially harmful for local populations who can face shortages in food supply.

Most of this literature is based on two main modelling approaches to estimate changes in agricultural output: statistical–econometric methods and process-based biophysical crop models (Estrada et al., 2012; Lobell et al., 2011; Nelson et al., 2014; Rosenzweig et al., 2013; Schlenker & Roberts, 2009). The advantages and shortcomings of these two approaches have been discussed in a variety of studies and in general conclude that they can produce informative, and complementary, estimates about the effects of climate change on agricultural productivity (Lobell & Burke, 2010; Roberts et al., 2017). Results from this literature have been included in damage functions of so-called integrated assessments models (IAMs) of climate change and the economy, which assess the broader economic welfare implications of various scenarios of greenhouse gas emissions and climate policy (Nordhaus, 2017; Stern, 2008). IAMs use stylized representations of different aspects of socioeconomic and climate systems, and their interactions, that permit modelling them as a whole and simulating their responses to external changes, such as the effects of climate policies (Diaz & Moore, 2017; Füssel, 2010). IAMs require highly simplified representations and low computational costs and aim to provide approximate, but insightful, results on climate change impacts to support decision-making (Nordhaus, 2013).

The assessment of the potential impacts of climate change in agriculture has greatly benefited from the adoption of econometric methods such as fixed-effects panel regressions. These models make use of variations in agricultural productivity and climate variables over time and space to estimate their relationships, while accounting for other variables that may affect these relationships (Baltagi, 2013). Recently, spatial panel models have been proposed to improve further the identification of causal relationships and the quality of predictions (Chakir & Lungarska, 2017; Goulard et al., 2017). When data occur in the geographical space, the state-of-the-art econometric methods are spatial panel models that include an ever-growing range of models that can account for the spatial and temporal characteristics of data. However, for some spatial panel models, the computational burden for high-resolution data over large spatial scales can increase rapidly and limit their application, as is discussed in the next section. In general, econometric methods have been limited to local and regional scales (Deschênes & Greenstone, 2007; Mendelsohn et al., 1994; Schlenker & Roberts, 2009). This is in part due to the requirements of local data needed to model appropriately some measure of productivity, such as crop yield, output and land value, and of data inputs such as general socioeconomic conditions, input and output prices, and climate variables. Recently, process-based models have been extended to produce global estimates of changes in agricultural productivity at the gridded level under different greenhouse gas emissions scenarios (Rosenzweig et al., 2013, 2014). These estimates have been used to improve the statistical–econometric projections (Roberts et al., 2017), and to produce crop-model emulators using panel regression models (Blanc, 2017).

The emulator models based on fixed-effects panel regressions can potentially reproduce very closely and efficiently crop-model output, mainly because crop models are deterministic, and their equations are already stylized representations of a limited number of processes, in comparison with observed agricultural productivity data (Rosenzweig et al., 2014; Van Ittersum & Donatelli, 2003). In fixed-effects models, the time-invariant characteristics of each grid cell that potentially influence agricultural productivity, such as soil and some environmental and social conditions, can be accounted for by a cross-section fixed-effects component. Furthermore, time-varying unobserved characteristics can also be included in the model by a two-way fixed-effect model with period and cross-section components. The projections from such models may further be improved by considering spatial dependence (Baltagi & Li, 2006).

The present study is closely related to Blanc (2017), who constructed global crop-model emulators for maize, soybean, wheat and rice at the grid cell level, based on fixed-effects panel models. However, the main objective of the present paper is to include simple crop emulators into an IAM that can produce individual and multivariate probabilistic projections and risk measures that may be helpful for supporting decision-makers and stakeholders. We use a different estimation approach to Blanc based on long-period averages to minimize the noise in yields generated by climate models' internal variability. Out-of-sample forecast performances of panel models based on both temperature and precipitation are analysed. A specification based only on temperature is proposed as a simplified approximation that is particularly convenient for IAMs of climate change, given that most IAMs only produce temperature projections. The inclusion of physical impact emulators that can produce tailor-made risk measures are an important extension of IAMs, which have been criticized for representing climate change risks in an incomplete, or ad-hoc manner (Stern, 2013; van den Bergh & Botzen, 2015). Moreover, global climate policy goals change over time, and there is a growing need to produce climate and impact scenarios for these potential trajectories for which simulations from complex climate models do not exist, but that can be produced by some IAMs to assist decision-making. Integrating crop emulators and IAMs can produce spatially explicit yield projections for climate scenarios not yet considered by the IPCC nor by the current large-scale projects of climate change impacts on agriculture, such as the AgMIP (http://www.agmip.org/).

We combine elements of statistical–econometric methods, process-based crop models, statistical simulation and the integrated assessment framework to propose a new IAM for uncertainty management and risk assessment of the physical impacts of climate change on agriculture at a refined spatial resolution. This IAM would help transforming the vast amount of crop-model simulation data into information that can be meaningful to decision-makers. Moreover, we provide a standalone application of the Assessment of Impacts and Risks of Climate Change on Agriculture (AIRCCA) model that can create individual and multivariate probabilistic impact scenarios and risk measures at a spatial resolution of $0.5 \times 0.5^{\circ}$ for three of the main global crops (rainfed maize, wheat and rice). AIRCCA makes use of an extensive collection of projections from physical climate models under unabated and policy climate change scenarios. It integrates a spatially explicit, low computational cost, reduced-form crop emulator with a module for generating probabilistic climate change scenarios, and an impact and risk estimation module. AIRCCA can be extended in future research to calculate the economic costs implied by the physical quantities modelled here.

The paper is structured as follows. The next section presents the climate and crop simulation data used for the study and briefly discusses the advantages of classical and spatial panel regression models for analysing the spatially explicit and time-varying nature of process-based crop and climate output. The estimated models are discussed in the third section, and their ability to reproduce the biophysical model projections is evaluated. A combination of the estimated models is proposed to minimize the root mean square error (RMSE) of the panel models' projections. The fourth section describes the structure of AIRCCA and how the emulator models are integrated. Probabilistic yield projections and risk measures are discussed in the fifth section. Conclusions and directions for future research are presented in the sixth section.

DATA AND METHODS

The climate scenarios and yield projections for rainfed maize, wheat and rice used for estimating the panel regression models were obtained from the AgMIP7 by means of the AgMIP Tool (Villoria et al., 2016). Yield projections come from the Environmental Policy Integrated Climate (EPIC) model (https://epicapex.tamu.edu/epic/). The temperature and precipitation projections used to build the emulator models are those of the HadGEM2-ES climate model used in the experiments included in the AgMIP7. Climate and crop projections have annual frequency and a spatial resolution of 0.5 × 0.5°.

The effects of the internal variability of climate models over yield projections are significant during the first four to five decades of the century, as well as for low emissions scenarios (Estrada, 2018). Since our interest relies on estimating the effects of the climate signal over the expected annual yields, to estimate the statistical models we use averages across the periods 2005–35, 2035–65 and 2069–99 for both yield and climate variables. This also helps to reduce potential heteroskedasticity, autocorrelation and cross-sectional dependence problems. This results in a balanced panel of 31,408 grid points and three time slices per emission scenario. We considered the scenarios of a single climate model since the estimated relationships are not expected to depend on the climate model, just on the changes in climate variables. Panel models were estimated for the four representative concentration pathways (RCPs), which represent different trajectories of greenhouse gas emissions that are named according to the radiative forcing level they will attain in 2100 (Meinshausen et al., 2011). These emissions scenarios are, from highest to lowest, RCP8.5, RCP6, RCP4.5 and RCP2.6. RCP8.5 and RCP6 commonly represent unabated warming scenarios, while RCP2.6 is considered consistent with the goals of the Paris Climate Accord. The different rates and trajectories of warming implied by each of these scenarios are expected to produce variations in the estimated coefficients.

A wide range of climate models' runs were gathered for estimating the probabilistic projections of crop yield changes and the associated risks measures in order to account for uncertainty in climate projections arising from climate modelling. These model runs are expressed as anomalies from the model's reference climate (1980–2005) and were obtained from the Royal Netherlands Meteorological Institute's Climate Explorer (https://climexp.knmi.nl). For the RCP8.5 scenario, 39 climate realizations were used, while for the RCP6, RCP4.5 and RCP2.6 scenarios the numbers of simulations were 21, 39 and 32, respectively (see Table S1 in the supplemental data online). Climate models' projections were interpolated to a common grid with spatial resolution of 0.5 × 0.5° using a nearest-neighbour method. Multimodel ensembles and probabilistic scenarios for climate change are highly debated topics, and different approaches have been proposed, including that applied here (Knutti et al., 2010; Sanderson et al., 2015; Weigel et al., 2010). As described in the fourth section, the probabilistic climate change scenarios are based on a uniform distribution which is used to select randomly the climate models' projection. The Climate Research Unit's (CRU) TS 4.01 data set for land temperature (https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.01/) was used to represent the observed climate over the reference period (1980–2005).

Fixed-effects panel models were used to estimate the effects of annual temperature over yields. The two-way fixed-effects model can be represented as:

$$Y_{it} = \beta_1 X_{1,it} + \cdots + \beta_k X_{k,it} + \alpha_i + \lambda_t + u_{it}$$

where Y_{it} is the dependent variable; $X_{k,it}$ is the k-th independent variable for the cross-section element i and time t; β_k is the slope parameter for the k-th independent variable; α_i is the intercept for the $i = 1, \ldots N$ cross-section element; λ_t is the period fixed effect for time $t = 1 \ldots, T$; and u_{it} is the error term.[1] The cross-section fixed-effects α_i account for time-invariant factors that have an effect over the element i and thus avoid the omitted variables bias problem in the cross-section dimension. The period fixed-effects λ_t captures the effects of unobserved/omitted variables that vary over time (such as CO_2, which has a fertilization effect over some crops), but which are constant cross-sectionally (Baltagi, 2013; Greene, 2012; Wooldridge, 2010). The nature of the relationship suggests the fixed-effects model to be preferable to the random-effects model, as the time-invariant characteristics of cross-sectional elements (e.g., soil, climatology) are expected to be correlated to $X_{k,it}$ and violate this random-effects assumption. The Hausman test is used formally to evaluate if the fixed-effects model is preferred to the random-effects model. Redundant variables tests evaluate if cross-section and/or period fixed effects are jointly insignificant, thus indicating that pooled ordinary least squares (OLS) models are preferable (Baltagi, 2013). As discussed in the next section, tests results indicate that fixed-effects models are adequate in all cases.

Spatial panel models are increasingly popular in empirical economic research and particularly useful for modelling spillover effects and externalities. The fixed-effects models can be extended to account for spatial dependencies such as interactions and structures (Baltagi, 2013). Of the ever-growing number of spatial panel models available, we considered the spatial lag regression (SAR) model, which is one of the simplest. In the SAR panel model, a spatial autoregressive term ρWY is included as an explanatory variable, where W is a spatial weight matrix and ρ is a spatial autoregressive coefficient. In our application, $N = 31,408$ and W is a 31,408 × 31,408 matrix (with almost 1 billion entries) that makes estimating spatial panel models computationally demanding.[2] Moreover, conducting simulation experiments to create probabilistic yield change scenarios using these models would be computationally prohibitive for most users. While forecast performance gains may be obtained, because of computational limitations, this is not compatible with the geographical scale and spatial resolution of the study and with the constraints imposed by its objectives (i.e., maintaining a complexity level similar to most of the common IAMs, making it suitable for probabilistic risk assessment and appropriate for the use of decision-makers/stakeholders with standard computing resources). We believe the implementation of spatial panel models to be a very valuable option for constructing crop emulators such as those presented here, but for smaller spatial domains (or for a coarser resolution) or for applications in which the use of supercomputing is considered. For these reasons, we do not pursue further in this paper the application of spatial panel regression models. Nonetheless, the following sections briefly discuss how their use could potentially improve the estimates and forecasts.

Two specifications for the fixed-effects model were estimated for modelling crop yields. The first specification (s1) uses linear and quadratic terms of temperature T_{it} and precipitation P_{it} and their cross product:

$$Y_{it} = C + \beta_1 T_{it} + \beta_2 T_{it}^2 + \beta_3 P_{it} + \beta_4 P_{it}^2 + \beta_5 P_{it} T_{it} + \lambda_t + \alpha_i + u_{it} \tag{s1}$$

The second specification (s2) is a simplified version of (s1) which includes only temperature and period fixed effects to control for the omission of P_{it}:

$$Y_{it} = C + \beta_1 T_{it} + \beta_2 T_{it}^2 + \lambda_t + \alpha_i + u_{it} \tag{s2}$$

The functional form in both specifications (s1) and (s2) is common in the climate change literature, because it is related to phenological concepts such as the existence of optimal values of climatic variables for crop growth (Deschênes & Greenstone, 2007; Estrada et al., 2012). The inclusion of interaction effects captures how variations in temperature and precipitation can have synergistic effects on yields.

The fixed-effects model for equations (s1) and (s2) uses the Least Square Dummy Variable (LSDV) estimator with absorbed variables (the *areg* function in Stata). Specifications (s1) and (s2) were estimated for each crop using four sets of Y_{it}, T_{it} and P_{it} that correspond to each RCP scenario. These regressions are denoted by s1-RCP2.6, s1-RCP4.5, s1-RCP6, s1-RCP8.5 and s2-RCP2.6, s2-RCP4.5, s2-RCP6, s2-RCP8.5 to represent each model specification (s1, s2) and RCP scenario (RCP2.6, RCP4.5, RCP6, RCP8.5).

Specification (s2) is of particular interest for its use in IAMs, since most of such models are driven only by temperatures, and because precipitation is harder to represent in the simplified framework of integrated assessment. For this reason and given the similarity in forecast performance between the two specifications, only the (s2) model will be considered to generate probabilistic scenarios and risk measures.

MODEL ESTIMATION AND FORECAST EVALUATION

Causality and prediction modelling are different, and internally consistent models need not outperform those that are not internally consistent when forecasting (Box et al., 1971; Hendry & Clements, 2003; Shmueli, 2010). Our application of panel models centres in emulating the forecast of biophysical crop models. Inefficiency and potential bias in regression coefficients that could be caused by misspecification errors is less of a concern since the focus is not on examining the statistical significance of estimated relations or hypothesis testing about coefficients (Shmueli, 2010).

However, the supplemental data online include some commonly used misspecification to assess the internal validity of the panel models and to justify the selection of fixed-effects specification (see Tables S2–S7 online). The misspecification tests applied are Hausman, redundant variables, heteroskedasticity and autocorrelation. The tests results are broadly similar for the (s1) and (s2) specifications. The fixed-effects model is preferred to random effects, as well as to pooled OLS. Moreover, the fixed-effects redundant variables test shows that a two-way fixed-effects model (cross-section and period effects) is needed to capture spatial and temporal heterogeneity in the data set. For both (s1) and (s2) models, tests suggest the presence of heteroskedasticity and autocorrelation, which implies that methods for estimating robust standard errors are required if the significance of the estimated coefficients should be evaluated.

Several studies have shown how accounting for spatial correlations in econometric models with spatial explicit data of, for example, agricultural land rent, improves the model fit (Chakir & Lungarska, 2017; Goulard et al., 2017). If spatial autocorrelation is present, ignoring it can result in inefficiency, bias in estimated regression coefficients and can affect prediction accuracy. Not modelling spatial autocorrelation can negatively affect out-of-sample forecast performance which is the objective of the estimated models in this paper. However, as discussed in the previous section, the objectives of this paper, the global domain and spatial resolution, make the use of spatial panel models impractical because of their computational costs. Nonetheless, the effect of not modelling spatial autocorrelation may be relatively small. It has been shown through Monte Carlo simulations that accounting for heterogeneity in panel models (by means of including random or fixed effects) produces large gains in forecast performance, but that the forecast performance is only slightly improved by additionally accounting for spatial autocorrelation (Baltagi, 2013; Baltagi et al., 2012). An empirical study that analysed the effects of spatial autocorrelation on out-of-sample forecasting in a panel regression model for liquor demand found that the differences between fixed- and random-effects specifications ignoring or including spatial autocorrelation were not significant, and in some cases the fixed-effects models without spatial autocorrelation outperformed the other specifications (Baltagi & Li, 2006). Moreover, as is discussed below, in our application out-of-sample error and bias proportion are in general small for the estimated models. Owing to computational constraints and considering the objectives of this paper, we refrain from using spatial panel models, although acknowledge that these models offer important advantages over traditional fixed/random-effects panel regressions.

Tables A1–A4 in the supplemental data online show the estimated regression coefficients and their statistical significance for each of the RCP data sets. Regardless of the method used to estimate robust standard errors, most coefficients are statistically significant at the 1% level (see Tables S8–S11 in the supplemental data online). This is expected as the yields are produced by a set of deterministic equations that are driven by these climate variables. As indicated by the R^2 and the adjusted R^2, the (s1) and (s2) specifications provide a very close fit to the EPIC projections. The differences in the magnitudes of the temperature coefficients across RCPs and across (s1) and (s2) specifications suggest the existence of multicollinearity caused by the inclusion of linear and quadratic terms of the explanatory variables and that precipitation has a relevant effect on yields. However, the small differences in goodness of fit between the (s1) and (s2) specifications suggest that the linear and quadratic terms of precipitation contribute marginally to the explanatory power of the model. Moreover, as described below, omitting precipitation has small effects on out-of-sample forecast performance.

Similar values of adjusted R^2 do not imply that models (s1) and (s2) have similar forecast performance. To evaluate this, the fixed-effects models based on specifications (s1) and (s2) were re-estimated by restricting the sample size to only the first two time horizons in order to evaluate their out-of-sample forecast performance using the third time horizon. We evaluated the forecast accuracy of the proposed models by calculating the RMSE and the Theil inequality coefficient (TIC) for the out-of-sample predictions. The TICs can range between 0 and 1, with 0 indicating the perfect forecast. This coefficient can be decomposed in three components: bias proportion, which indicates how far the mean of the forecast is of the mean of the actual series; the variance proportion, which indicates how far the variance of the forecast is from the variance of the actual series; and the covariance proportion, which measures the remaining unsystematic forecast errors, in which a value close to 1 would indicate the remaining forecast errors are noise which does not affect the forecast performance.

As shown in Table S12 in the supplemental data online, the forecast performance is very similar for both specifications (s1) and (s2), being only slightly better for (s1) in most cases. The exceptions are equations s2-RCP4.5, s2-RCP8.5 for wheat and s2-RCP8.5 for rice. In comparison with specification (s2), the RMSE of (s1) is on average 6.5%, 0.5% and 8.5% smaller for maize, wheat and rice, respectively. As expected, the forecast performance depends on the RCP scenario. In terms of RMSE and relative root mean squared error (RRMSE, i.e., RMSE divided by the range of the dependent variable), the forecast tends to be better for the RCPs that imply lower levels of warming. The forecasts with lowest RRMSE are those of the RCP2.6 scenario, and the RRMSE increase for all other scenarios. Nevertheless, the differences between mid- and high-warming scenarios (e.g., RCP4.5 and RCP8.5) are relatively small. As revealed by the

RRMSE, forecast errors are considerably smaller than the variability of yields, suggesting that they are reasonably small (Ray et al., 2015). In all cases, the TIC is low and very similar between the specifications (s1) and (s2). Moreover, the forecasts tend to have a covariance proportion close to 1 with bias and variance proportions close to 0. The highest values of bias proportion occur for the regressions based on the RCP4.5 and for high-warming scenarios (RCP8.5 and RCP6) for wheat. The use of spatial panels could probably decrease the bias proportion, but the results shown in Table S12 in the supplemental data online suggest that the forecast bias is not large for most of these models. Overall, the goodness-of-fit measures and the forecast performance evaluation indicate that specifications (s1) and (s2) produce similar results. However, (s2) has the important advantage that it depends only on temperature projections, which are easier to produce in an integrated modelling framework. Thus, we consider the parsimonious specification (s2) to be more desirable for the objective of constructing a reduced-form emulator of yields of rainfed maize, wheat and rice produced by the EPIC model.

For models (s2), we conducted a cross-validation analysis to evaluate which (s2) regressions produce more general forecasts and which of them perform better for near-, mid- and long-term horizons. The performance of the estimated regression equations based on specification (s2) was also evaluated across the different RCP scenarios, using the coefficients estimated for the full sample. Tables S13–S15 in the supplemental data online show the RMSE of the forecasted yields obtained from the regression models fitted to the four RCP sets of Y_{it}, T_{it} and the EPIC model's projected yields. None of the estimated equations produces the best fit for all RCP emissions scenarios and horizons, but there are similarities across RCPs and crops. Regardless of the RCP emissions scenario, the s2-RCP2.6 produces the smallest RMSEs for the short-term horizon (2005–35). For most cases, the best forecasts for the medium- and long-term horizons (2035–65, 2069–99) are obtained by applying the regression equation that matches the emission scenario (e.g., equation s2-RCP8.5 for the RCP8.5 scenario). The exceptions are for the combinations of the RCP6 emission scenario and maize and wheat yields, in which the long-term horizon is better forecasted using the s2-RCP8.5 equation.

To emulate as closely as possible the EPIC model, the estimated equations are combined to minimize the RMSE for each of the RCP emissions scenario. These combinations of equations define the emulation models for each crop and RCP scenario that will be used in the next section. For example, the emulating model for wheat under the RCP8.5 consists of the s2-RCP2.6 for the short-term horizon, and the s2-RCP8.5 equation for the medium- and long-term scenarios (see Table A5 in the supplemental data online).

Note that the application of these emulation models can be generalized to other emissions scenarios if they are interpreted in terms of the level of warming and time horizons: for low-warming scenarios, such as those produced by strong international mitigation efforts, the s2-RCP2.6 regression equation provides the best approximation; for moderate-warming scenarios, the combination of the s2-RCP2.6 for the short-term horizon and the s2-RCP4.5 or s2-RCP6 for the medium- and long-term horizons are best; while for high-warming scenarios, the combination of the s2-RCP2.6 for the short-term horizon and the s2-RCP8.5 for the medium- and long-term horizons would produce better projections.

AIRCCA: AN INTEGRATED MODEL FOR THE ASSESSMENT OF THE IMPACTS AND RISKS OF CLIMATE CHANGE ON AGRICULTURE

To illustrate the use of the crop model emulators in the context of integrated assessment modelling, we integrate the crop emulator models developed in the previous section into a global climate change impact assessment model called the Assessment of Impacts and Risks of Climate Change on Agriculture (AIRCCA). AIRCCA is a simulation model for generating probabilistic projections of yield change as well as user-defined risk measures for the main three global crops: maize, wheat and rice. The user can select preferred outputs of results for the main four RCP emission scenarios, and examine results that are visualized on world maps or zoom in to obtain detailed results for a region of interest. For the standalone AIRCCA software, see https://sites.google.com/view/aircc-lab/.

Figure 1 presents a schematic representation of the structure of AIRCCA. This model has three components: the climate module (Figure 1(a)), the crop emulator module (Figure 1(b)), and the risk and impact module (Figure 1(c)). The climate module contains a database of temperature-change projections from a large number of climate models included in the IPCC's Fifth Assessment Report (Stocker et al., 2013). These scenarios are constructed for three time horizons (short, medium and long term) and for the four RCP scenarios. The temperature change scenarios are stored in three-dimensional matrices $M_{i,j,m}^{RCP,H}$ in which the first two dimensions i, j refer to geographical coordinates and the third one, m, indicates the climate model simulation, while the superscripts denote the emissions scenario RCP and the time horizon H, respectively. Once an RCP scenario and a time horizon are selected by the user, the temperature projections from the database are randomly selected using a uniform distribution with support ranging from 1 to R, the total number of climate models' runs available for the chosen RCP scenario. The future temperature projection at the grid cell level is obtained by adding the changes projected by the climate model to the observed reference climate (CRU TS 4.01), as follows:

$$T_{ij}^{RCP,H,m'} = T_{ij}^{O} + M_{ijm=m'}^{RCP,H}$$

where m' is a realization from the uniform distribution $U(1, R)$; R is the number of climate model simulations available for the selected RCP; and T_{ij}^{O} is the reference climatology.

The crop emulator module uses the observed climatology and the future temperature scenarios to produce the corresponding crop yield scenarios. The baseline $Y_{ij}^{C,base}$ and future $Y_{ij}^{C,RCP,H,m'}$ yield

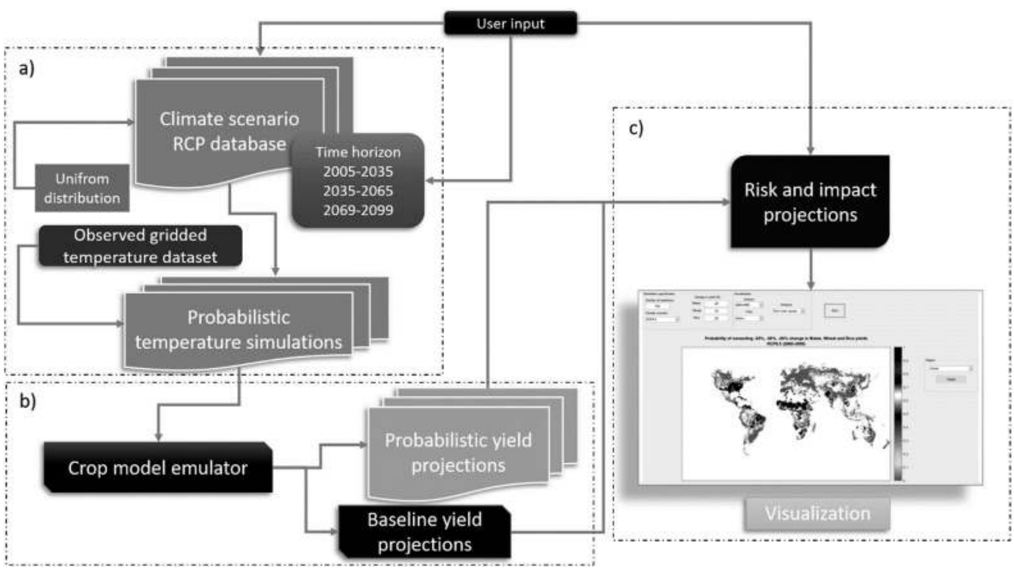


Figure 1. Schematic representation of the structure of the Assessment of Impacts and Risks of Climate Change on Agriculture (AIRCCA) model.

scenarios for crop C are obtained by including T_{ij}^{O} and $T_{ij}^{RCP,H,m'}$, respectively, in equation (s2):

$$Y_{ij}^{C,base} = C + \beta_1 T_{ij}^{O} + \beta_2 (T_{ij}^{O})^2 + \lambda_t + \alpha_i$$
$$Y_{ij}^{C,RCP,H,m'} = C + \beta_1 T_{ij}^{RCP,H,m'} + \beta_2 (T_{ij}^{RCP,H,m'})^2 + \lambda_t + \alpha_i$$

and the percentage change in yields for the grid point i,j is calculated as:

$$\Delta Y_{ij}^{C,RCP,H,m'} = (Y_{ij}^{C,RCP,H,m'} / Y_{ij}^{C,base} - 1) * 100.$$

The operations in the climate and crop emulator modules described above are repeated S times and the percentage change in yields is stored in three-dimensional matrices $\Delta Y_{ijs}^{C,RCP,H}$, where the dimension $s = 1, \ldots, S$ represents the crop yield simulation. For the examples presented here, $S = 1000$ repetitions were used.

In the risk and impact module, the three-dimensional matrices $\Delta Y_{ijs}^{C,RCP,H}$ are used to produce the following measures:

- The mean percentage change of potential yields for each grid cell. The mean percentage change is calculated as:

$$\overline{\Delta Y}_{ij}^{C,RCP,H} = \frac{\sum_{s=1}^{S} \Delta Y_{ijs}^{C,RCP,H}}{S}$$

- The probability of exceeding a user-defined threshold in the percentage change of potential yields w^C for crop C, at the grid cell level. First, the indicator function $I(\cdot)$ is used to find the grid cells in which the condition of exceeding w^C is met:

$$Tr\Delta Y_{ijs}^{C,RCP,H} = \begin{cases} I(\Delta Y_{ijs}^{C,RCP,H} > w^C) & \text{if } w^C > 0 \\ I(\Delta Y_{ijs}^{C,RCP,H} < w^C) & \text{othewise} \end{cases}$$

where $Tr\Delta Y_{ijs}^{C,RCP,H}$ is a three-dimensional matrix of zeros and ones that denotes in which cases the threshold has been exceeded. These probabilities are calculated as follows:

$$P(\overline{\Delta Y}_{ij}^{C,RCP,H} \text{ exceeding } w^C) = \frac{\sum_{s=1}^{S} Tr\Delta Y_{ijs}^{C,RCP,H}}{S}$$

- The probabilities of jointly exceeding the thresholds selected by the user for maize, wheat and rice. This multivariate risk index is calculated in two steps. First, the indicator function $I(\cdot)$ is used to find the grid cells in which all thresholds are exceeded:

$$Tr\Delta Y_{ijs}^{RCP,H} = I[(Tr\Delta Y_{ijs}^{C=1,RCP,H} + Tr\Delta Y_{ijs}^{C=2,RCP,H} + Tr\Delta Y_{ijs}^{C=3,RCP,H}) > 2]$$

where $C = 1, \ldots, 3$ represents maize, wheat and rice, respectively. The probabilities are calculated as:

$$P(\overline{\Delta Y}_{ij}^{C,RCP,H} \text{ jointly exceeding } w^{C=1}, w^{C=2}, w^{C=3}) = \frac{\sum_{s=1}^{S} Tr\Delta Y_{ijs}^{RCP,H}}{S}$$

- The hotspot multivariate risk index: it gives each grid cell a value between 0 and 3 that represents how many individual thresholds in yield changes have been exceeded. It shows the geographical areas where these risks converge. In AIRCCA, a threshold is considered to be reached if the estimated probability is larger than $\gamma = 50\%$. This index is calculated for each grid cell as the weighted sum of thresholds that have been exceeded according to this criterion:

$$H\Delta Y_{ij}^{RCP,H} = I(P(\overline{\Delta Y}_{ij}^{C=1,RCP,H} \text{ exceeding } w^C) > \gamma) + I(P(\overline{\Delta Y}_{ij}^{C=2,RCP,H} \text{ exceeding } w^C) > \gamma) + I(P(\overline{\Delta Y}_{ij}^{C=3,RCP,H} \text{ exceeding } w^C) > \gamma)$$

- Finally, the risk and impact module includes a visualization interface that allows the user to explore the consequences of different climate change scenarios on these three main agricultural crops at the global and regional scales, with a spatial resolution of 0.5 × 0.5°. Section B in the supplemental data online provides an installation guide for the AIRCCA standalone, as well as a short description of how to use it.

EXPLORING THE IMPACTS AND RISKS OF CLIMATE CHANGE FOR RAINFED MAIZE, WHEAT AND RICE UNDER DIFFERENT RCP SCENARIOS

In this section we explore the effects of climate change on the potential yields of rainfed maize, wheat and rice at the global scale for an unabated emissions scenario (RCP6) and a policy scenario that is consistent with the compliance of the Paris Climate Accord (RCP2.6). The analysis focuses on the medium and long horizons, but through AIRCCA the reader can explore other emissions scenarios (RCP8.5, RCP4.5) and the short-term horizon. The results are based on simulation experiments of 1000 repetitions, and a 20% decrease in yields is defined as the relevant risk threshold for all crops.

Figures S1 and S2 in the supplemental data online show the mean percentage change for potential yields for maize, wheat and rice, under the RCP6 scenario for the medium and long horizons. Unabated climate change implies important changes in the current distribution of areas suitable for rainfed production of these crops. The spatial patterns of changes in potential yields show some similarities between crops, and that the most affected regions tend to be located within a latitude band from 20°S to 40°N. The reductions in potential yields would become larger towards the end of the century and the magnitude of changes range from 10% to 30% with respect to the reference climate (1980–2005). Some parts would experience much larger decreases in yields, including the south central and eastern parts of the United States, northern Africa, Sub-Saharan Africa, Middle East, Mongolia and the eastern tropical region of South America.

For large areas in Europe, the changes in climate produced under the RCP6 could lead to higher potential yields, particularly in the case of wheat and rice, with yields increasing up to 20%. However, Spain and Portugal could be negatively affected with decreases in the potential yields of all crops during this century. For maize and rice, high-latitude regions in the Northern Hemisphere and small areas in China, India and Russia could experience important increases in potential yields. Figures S3 and S4 in the supplemental data online show the mean percentage change for potential yields for maize, wheat and rice, under the RCP2.6 scenario which is consistent with the goals of the Paris Climate Accord. The implementation of this scenario would significantly reduce the losses in potential yields across the world. Moreover, since mid-century, the moderate warming of the RCP2.6 could imply considerable increases in potential yields of maize and rice for some high-latitude regions. However, in the case of wheat, substantial decreases in yields would still occur in large parts of the United States, South America, Africa, Asia and Middle East.

A more informative way to handle the uncertainty in climate projections and to communicate it is through probabilistic impact scenarios and the use of risk measures. As described above, AIRCCA produces two types of risk measures based on thresholds defined by the user: uni- and multivariate probabilities of exceeding predefined thresholds and a hotspot index that shows where the risks converge (i.e., areas where the different thresholds are exceeded). These measures can help decision-makers to understand better the risks of climate change and design adaptation strategies.

Figures S5–S8 in the supplemental data online show the probabilities of exceeding the threshold of a −20% in yields for each crop, while the probabilities for jointly exceeding these thresholds are shown in Figures S9 and S10 online. Overall, the probabilities of exceeding the selected thresholds under the RCP6 scenario tend to increase rapidly during the century, but projections show large variability in space, time horizon and crop. This is partly due to regional temperatures' variability and to the uncertainty in climate projections which increases with time. These figures illustrate that risk is the result of dynamic processes and that it evolves through time and space. In the medium horizon, the probability of exceeding a 20% loss in maize yields is close to unity for areas in some of the largest producers (United States, Mexico and India); for wheat, the probability of a decrease of at least 20% in yields is high for some parts of countries that contribute significantly to the world's crop productions, such as the United States, Russia, Canada and India. In the long horizon, the areas with high probabilities of exceeding this threshold tend to increase in those countries and others such as Canada, Brazil and China; the probabilities of reductions of more than 20% in rice yields are small in the largest producing countries during the medium horizon, but they rise to 50% or more during the last part of the century for regions of China, India and Brazil. The probabilities of jointly exceeding a reduction of at least 20% in these three crops suggest that both regions that currently account for a large share of the world's grain production (e.g., United States, Brazil and China), as well as regions that depend on subsistence agriculture (e.g., parts of Mexico, Central and South America, Sub-Saharan Africa) are likely to suffer important decreases in productivity because of climate change. This is especially the case towards the end of the century. Except for wheat and some small regions, the probabilities of exceeding decreases in yields larger than 20% can be greatly reduced if a policy scenario such as the RCP2.6 is achieved.

The spatial location of risk hotspots worldwide and their evolution in the medium- and long-term horizons for the RCP6 and RCP2.6 scenarios are shown in Figures 2 and 3. By mid-century, under the RCP6 the areas with the highest risk hotspot indices are limited to parts of the central and eastern United States, Venezuela, northern and Sub-Saharan Africa, and South Asia (Figure 2(a)). However, in significant parts of the world, particularly in South America and Africa, at least one of the main grain crops would show a decrease exceeding 20% in potential yields. Moreover, even if a strong international mitigation scenario is achieved, the level of risk in these regions would hardly decrease, underlying the importance of developing adaptation strategies (Figure 2(b)). Such a policy scenario would nonetheless significantly reduce the high levels of risk projected for regions of the United States, as well as the moderate level of risk projected for some parts of China and Russia. By the end of the century, the risk hotspots would expand significantly under the RCP6 scenario (Figure 3(a)). This is particularly noticeable for North America, and to a lesser extent for South Asia and Australia. In this case, the fulfilment of the Paris Climate Accord would lead to much smaller risk values, similar to those during the mid-century under the RCP2.6, making adaptation more realistic and easier to implement (Figure 3(b)).

Overall, unless significant efforts for reducing greenhouse gases emissions are undertaken, the production of rainfed crops could be severely reduced worldwide during this century. While the literature has shown that endogenous economic responses to climate change effects on agricultural productivity and the availability of new harvest areas can limit changes in consumption and yield loss, prices can significantly increases in response to yield reductions which negatively affects consumer welfare (Nelson et al., 2013). Moreover, the large spatial heterogeneity in the effects of climate change on agriculture revealed by the results, in combination with the socioeconomic conditions in some countries, could affect food security at the local and country level scales (Murray-Tortarolo et al., 2018; Ramirez-Cabral et al., 2017; Schlenker & Lobell, 2010).

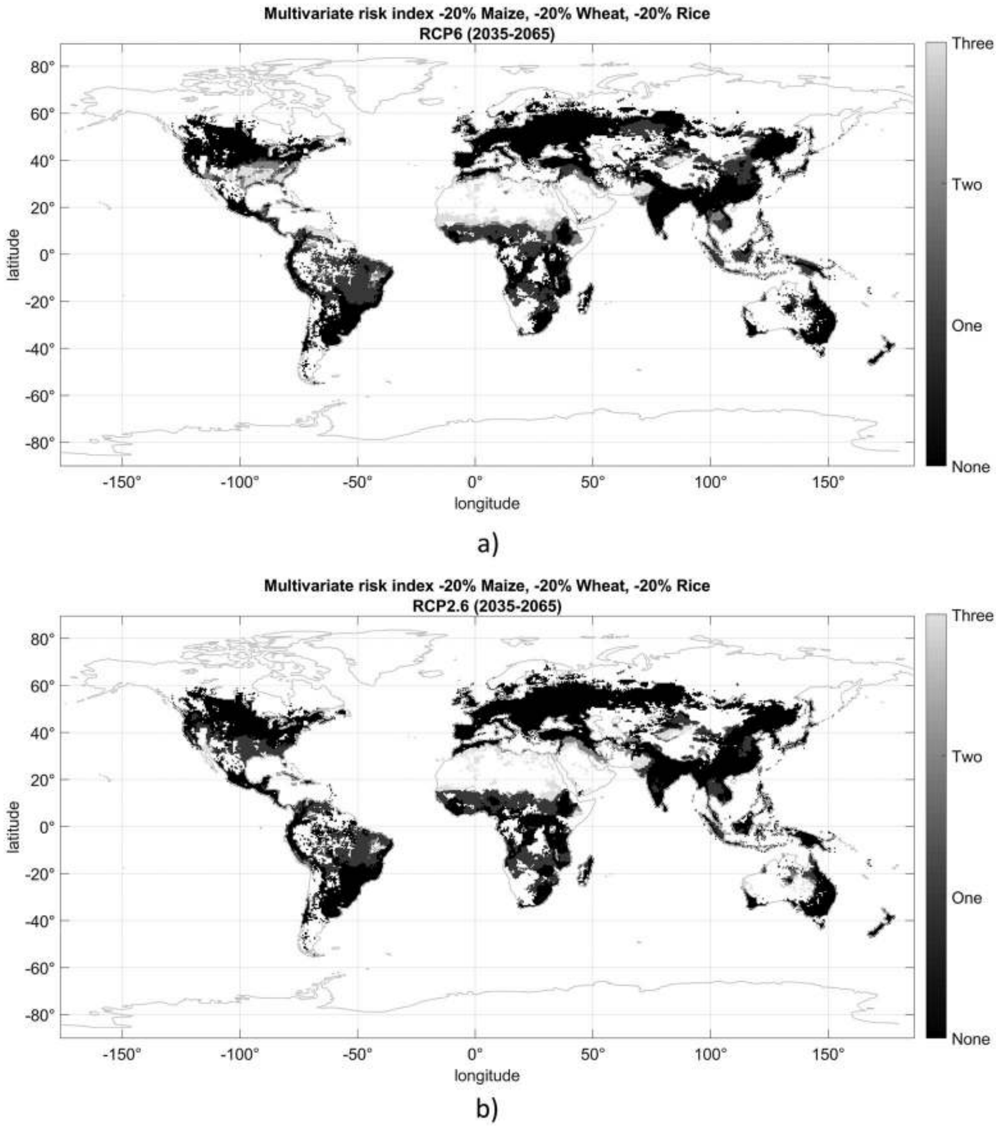
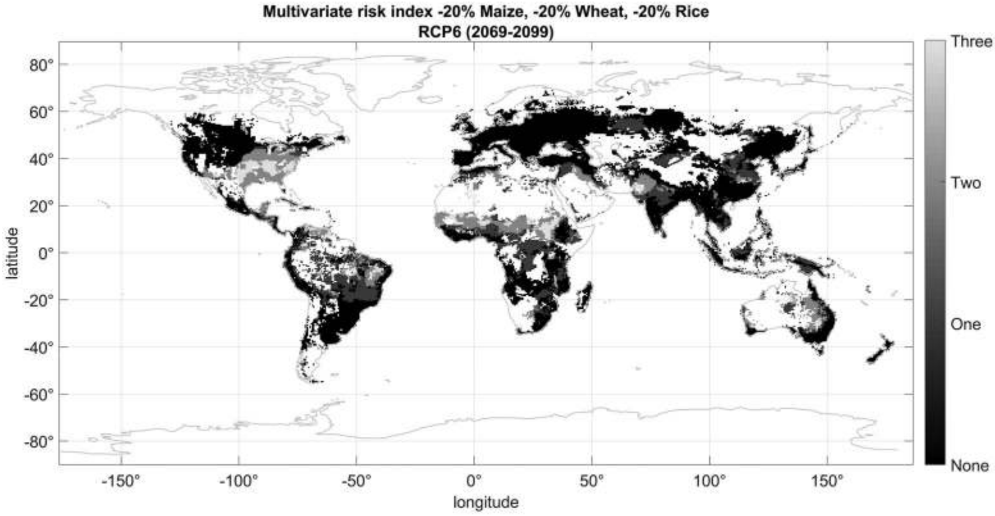


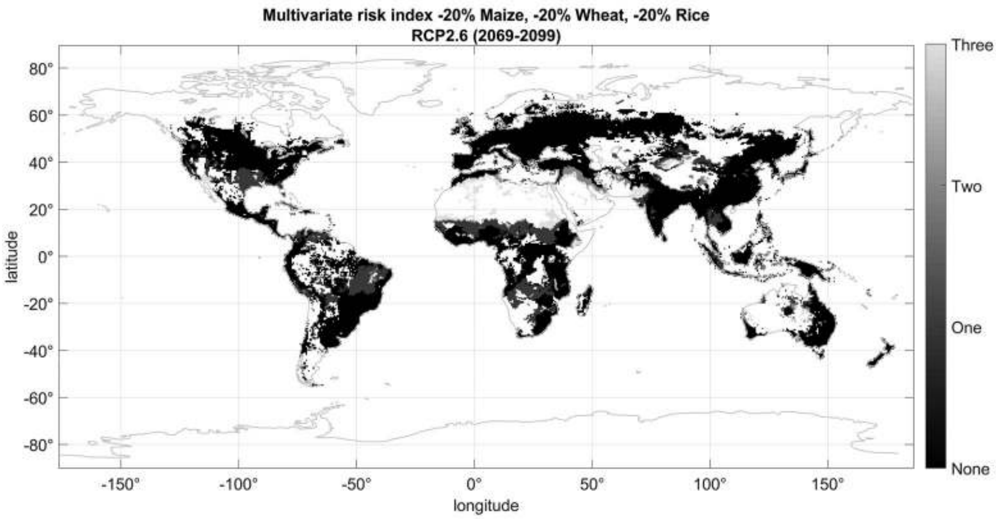
Figure 2. Hotspot risk index for the medium horizon (2035–65), computed for decreases of at least 20% in the yields of rainfed maize, wheat and rice and $\gamma = 50\%$: (a, b) hotspot index for the RCP6 and the RCP2.6 scenarios, respectively. White areas represent oceans and places for which the Environmental Policy Integrated Climate (EPIC) model does not consider the production of these crops possible.

CONCLUSIONS

Previous studies suggest that agriculture is the economic sector that would be most affected by climate change, and that these changes in agricultural productivity could significantly impact food security. However, many previous studies and models on this topic do not offer insights into the full spectrum of risks climate change poses for different crop yields under the wide range of possible climate change scenarios, and the spatial variability of these impacts and risks. Here we show that reduced-form emulators can be used for producing probabilistic projections



a)



b)

Figure 3. Hotspot risk index for the medium horizon (2069–99), computed for decreases of at least 20% in the yields of rainfed maize, wheat and rice and $\gamma = 50\%$: (a, b) hotspot index for the RCP6 and the RCP2.6 scenarios, respectively. White areas represent oceans and places for which the Environmental Policy Integrated Climate (EPIC) model does not consider production of these crops possible.

of the impacts of climate change on crop yields for the whole world at a refined spatial resolution of $0.5 \times 0.5°$. The proposed panel regression models fit very closely the projections by the more complex EPIC model. Moreover, the estimated models have good forecast performance, in particular when the different panel models are combined optimally for projecting low, medium and high warming. Importantly, the proposed emulators are driven exclusively by annual temperature changes that facilitate their integration into IAMs of climate change and the economy. We illustrate this use by developing a simulation model called AIRCCA that integrates the CMIP5 climate simulations and the reduced-form emulator models developed to produce probabilistic impact estimates and risk measures of the impacts of climate change on crop yields for three main global crops: rainfed maize, wheat and rice. All estimates are produced at the local scale and can be used to address particular concerns of stakeholders as well as to help communicate the potential consequences of climate change and related uncertainties. The AIRCCA model is freely available at https://sites.google.com/view/aircc-lab as a standalone software. This user-friendly software can be used by stakeholders who aim to obtain a rapid assessment of climate change impacts and risks for agriculture in their region of interest, and allows for exploring different metrics fine-tuned by the user as well as to compare the implications of a variety of scenarios.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

NOTES

[1] In the models, the period fixed-effects component is modelled using two dummy variables: one for the period 2035–65, the other for 2069–99.
[2] Estimating SAR and spatial error models in STATA 16 SE and in the MATLAB panel data toolbox (https://nl.mathworks.com/matlabcentral/fileexchange/51320-panel-data-toolbox-for-matlab; https://ideas.repec.org/a/jss/jstsof/v076i06.html) was not feasible because of an out-of-memory problem using a computer with an Intel Core i7-6700 CPU processor (at 3.4 GHz), 32 GB of RAM and Ubuntu 16.04.6 LTS operating system.

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