Agricultural and Forest Meteorology 256–257 (2018) 46–52

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

Can we use crop modelling for identifying climate change adaptation options?

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ARTICLE INFO

Keywords:
Adaptation
Climate change
Climate models
Crop modelling
Crop yield
Uncertainty

ABSTRACT

Climate model projections coupled with process-based crop models are advocated for assessing impacts of climate change on crop yields and for informing crop-level adaptations. However, most reported studies are vague on the choice of the global circulation models (GCMs) for climate projections, and on the corresponding uncertainty with this type of model simulations. Here we investigated whether climate-crop modelling can be used for identifying crop management-level adaptation options. We focused our analyses on a case study for maize in southern Africa using the APSIM crop growth model and projections from 17 individual climate models for the period 2017–2060 for the contrasting representative concentration pathways 2.6 and 8.5. Intensification of nitrogen fertiliser use (from 30 to 90 kg N ha^{-1}) was simulated as an example of a crop management-level adaptation to climate change. Uncertainties in crop yield predictions were about 30 to 60%, i.e. larger than expected crop responses to most management-level interventions or adaptations. Variation in simulated yields was caused by inter-seasonal rainfall variability and uncertainty with climate models. Some GCMs resulted in significantly different maize yield predictions, without any clear pattern across sites. Given these high uncertainties, we argue that crop modellers should be cautious when informing future crop management adaptation strategies based on climate-crop model ensembles. A better use of crop models is the simulation of crop responses to current weather variability aiming at the identification of crop management practices for coping with climate variability. Promising practices can then be evaluated with farmers on their feasibility over a range of plausible future biophysical and socio-economic farming conditions.

1. Introduction

Climate change will affect crop production (Lobell and Gourdji, 2012). To study this and to quantify the effects, process-based crop growth models driven by projections of future weather are commonly used (e.g. Challinor et al., 2009a; White et al., 2011). The main source of weather projections are the Coupled Model Intercomparison Project -Phase 5- (CMIP5) model simulations (Ramirez-Villegas et al., 2013). The global circulation models (GCMs) used for these simulations are, however, highly complex and contain many inherent uncertainties (Mearns, 2010). They have resolutions typically of the order of a hundred kilometres, disparate from crop growth models that operate at the smaller scale of the field. To project local climate change that can be used with crop models at field scale, data from GCMs are downscaled using a variety of methods (e.g. Fowler et al., 2007). This entails further uncertainties and potential bias in projections (Wilby et al., 1998; Ramirez-Villegas and Challinor, 2012).

A growing number of studies use local climate model projections coupled with crop growth models to inform crop management-level adaptation options to climate change, such as altering planting dates and densities, cultivars and crop species, fertiliser regimes and crop rotations or associations, and quantify their impact on crop yields (Fig. 1) (e.g. Challinor et al., 2009b; Traore et al., 2017; Waha et al., 2013). Matthews et al. (2013), for example, argued that crop modelling can contribute to climate change adaptation by identifying which future crop management practices will be appropriate.

Most reported studies that assess impacts of climate change on crop production are vague on the choice of the GCM(s) for their future climate projections. Some studies have tried to identify the 'best' GCM or set of GCMs for a particular region or location of interest by comparing model outputs with historical weather data (e.g. Samadi et al., 2010). However, it seems that selecting GCMs based on the quality of their climate simulation in a particular location does not result in conclusions that are systematically different from those obtained by choosing

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https://doi.org/10.1016/j.agrformet.2018.02.026
Received 13 November 2017; Received in revised form 19 February 2018; Accepted 23 February 2018
0168-1923/

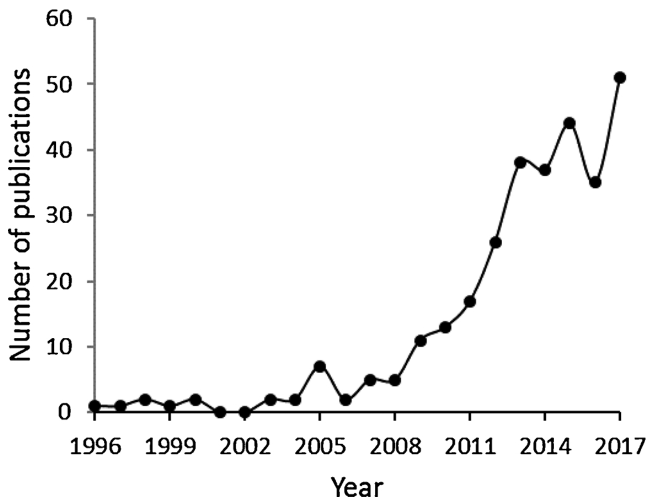

Fig. 1. Evolution of the number of papers published on studies coupling local climate model projections with crop models to inform and quantify impacts of adaptation strategies to climate change. Search string used in Scopus was: ("climate change" OR "changes in climate") AND "crop*" AND "model*" AND "adapt*" AND ("downscal*" OR "local*"), whereby an asterisk is a replacement for any ending of the respective term.

models randomly (Pierce et al., 2009). Moreover, a limited number of GCMs may not produce a representative range of plausible future climate projections (Ruane and McDermid, 2017). Studies increasingly use multi-GCM ensembles to cover the range of possible outcomes and to deal with uncertainties in future climate projections (Challinor et al., 2009b; Guan et al., 2017). The variability of the results from the models in the ensemble is a measure of the uncertainty as to how to model the system.

To investigate the extent to which GCMs can be used for estimating future crop yields, and more specifically, for identifying local crop management-level adaptation options to climate change, we used climate projections from 17 individual climate models that were part of the IPCC's Fifth Assessment Report (CMIP5; IPCC, 2013) (Table S1 in the Supplementary materials). We focused our analyses on simulating maize (*Zea mays* L.) grain yields at four locations in southern Africa, representing different agro-ecological conditions. Maize is the major staple food crop in that region, mainly produced with low level of nutrient inputs by smallholder farmers. Southern Africa is one of the hotspot for climate change in Africa, where climate change has been predicted to severely impact food security (Lobell et al., 2008).

2. Methods

Four sites were selected in southern Africa where long-term field experiments with maize are being conducted by CIMMYT (International Maize and Wheat Improvement Centre) (Table S2, Supplementary materials). These are: the Monze Farmer Training Centre, Zambia (16°14′27″S, 27°26′31″E, 1108 m), the Sussundenga Research Station, Mozambique (19°19′1″S, 33°14′27″E, 608 m), the Chitedze Research Station, Malawi (13°58′22″S, 33°39′14″E, 1145 m), and the Domboshawa Research Station, Zimbabwe (17°36′25″S, 31°8′27″E, 1543 m). The climate at the sites is tropical wet and dry (Aw, Köppen Climate Classification) with a unimodal rainfall pattern. Average annual rainfall is 750 mm at Monze, 1090 mm at Sussundenga, 960 mm at Chitedze and 880 mm at Domboshawa. Soils are Lixisols (Domboshawa and Sussundenga) and Luvisols (Chitedze and Monze), with distinct plant available water capacities, and fertility levels as indicated by the different soil carbon contents (Table S2, Supplementary materials). A detailed description of sites and experiments can be found in Thierfelder et al. (2013).

Simulated downscaled weather data (solar radiation, maximum and minimum temperature, and rainfall) for the four sites were obtained using the MarkSim GCM tool (http://gisweb.ciat.cgiar.org/MarkSimGCM, Jones and Thornton, 2013). MarkSim is a spatially explicit daily weather generator that uses a third order Markov chain process to generate daily rainfall, radiation, and temperature. The simulated period was 2010–2060 for the highly contrasting representative concentration pathways (RCPs) 2.6 (lowest emissions) and 8.5 (highest emissions). Mean seasonal temperature and cumulative seasonal rainfall were calculated based on a pre-defined length of the cropping season, i.e. from the 1st October to the 31st May of the following year.

We used the crop model APSIM, version 7.5 (Agricultural Production Systems sIMulator). APSIM simulates crop development and growth at a daily time step as a function of weather conditions, soil properties and management practices, such as chemical fertiliser and organic matter application, planting density and date, cultivar characteristics and tillage (through simulated soil water and nitrogen limitations to plant growth). A detailed description of the model can be found in Keating et al. (2003). The model was parameterized for maize growth (medium-duration cultivars, i.e. with a growing cycle of ~120 days) at the four sites using the data from the long-term experiments (Thierfelder et al., 2013). The APSIM maize cultivar-specific parameters are listed in Table S3, Supplementary Materials. The parameterized APSIM model was then used to simulate the response of maize to climate change at the four sites for the period 2017–2060 under the two emission scenarios, RCP2.6 and 8.5. Two levels of nitrogen fertilisation were simulated: 1) 15 kg N ha^{-1} at sowing and 15 kg N ha^{-1} as topdressing 35 days after sowing, and 2) triple dose, i.e. 45 kg N ha^{-1} at sowing and 45 kg N ha^{-1} as topdressing. The model was reinitialised at the start of each year's run to make the simulations independent, i.e. for each year the soil water, carbon and nitrogen variables were reset to the initial values. Sowing date was defined as the last day of three continuous days with rainfall accumulation of 20 mm within the defined sowing window of 1 October to 31 December. The crop response to CO_2 was not included, because the CO_2 fertilisation effect on photosynthesis in C4 crops is minor and the secondary effect of reducing crop transpiration is not well captured in crop growth models such as APSIM (Durand et al., 2018). For all simulations, CO_2 concentrations were held constant at 330 ppm.

GCM effects on mean seasonal temperature, cumulative seasonal precipitation and simulated maize grain yields were estimated using ANOVA procedures and pairwise comparisons (Tukey's HSD test at $P < 0.05$). A factorial decomposition of the APSIM model response was calculated using a general linear model with fixed terms to determine how sensitive the simulated yield output is with respect GCM, emission scenario, year (cropping season) and management (nitrogen fertilisation) for each location. A sensitivity index (SI) for a factor or interactions of factors was calculated as the ratio of the sum of squares associated with the factor or interaction of factors over the total sum of squares of simulated yield data, i.e. the total variability in the model responses (see equations in Table S4, Supplementary materials). The analyses were done with PROC GLM in SAS (version 8.02).

3. Results

3.1. Climate change predictions

Predicted changes in seasonal mean temperature were highly variable largely depending on the GCM used and the study site. Overall, across the four sites they varied under RCP2.6 from −0.2 °C for BCC-CSM1-1 at Monze to +1.5 °C for GFDL_CM3 at Domboshawa, and under RCP8.5 from +1.0 °C for BCC-CSM1-1 at Domboshawa to +3.0 °C for MIROC-ESM at Domboshawa (Fig. 2). As expected, temperatures were predicted to become warmer under RCP8.5 compared with RCP2.6. The variation in temperature changes for a given GCM was higher in Domboshawa and Monze than in Chitedze and Sussundenga, as indicated by the size of the circles in Fig. 2. Predicted changes in seasonal