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Projecting climate change impacts on grain maize based on three different crop model approaches

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ABSTRACT

Decision making in climate change adaptation planning depends on the quantification and broad understanding of uncertainties in projected climate impacts. In a case study, we estimated impacts of climate change on potential grain maize yield up to the time horizon 2036–2065 for three climatic regions in Switzerland using – for the first time – three fundamentally different impact modelling approaches: a process-based, a statistical and an expert-based approach. The aim was to quantify uncertainties originating from climate model chains, downscaling weather generator choice, and impact model parameterization. We find that while estimated climate impacts on yields are subject to large uncertainties originating from both climate model chains and impact model approaches, estimates of changes in crop-specific climate limitations are less ambiguous. We conclude that by subtracting the layer of uncertainty related to the aggregation of different climate influences on yield estimates and by focusing on estimated changes in climate limitations, more decision-relevant information can be provided to support crop-specific adaptation planning.

1. Introduction

The assessment of uncertainties in agricultural climate impact studies has gained increasing attention in recent years. Since estimates of impacts of projected climate changes on agricultural productivity are intended to support decision-making in adaptation planning, it is desirable to increase confidence in these estimates by providing as much information on known uncertainties as possible (Challinor, 2009; Challinor et al., 2013; Vermeulen et al., 2013). Quantifying and separating different sources of uncertainty helps to improve understanding of uncertainties in impacts and to derive decision-relevant information (Challinor et al., 2013).

A common approach to quantify uncertainties in impact estimates is to use ensembles, where impacts are estimated repeatedly with different models or different realizations of uncertain inputs. Using multiple climate projections as inputs has become a common procedure for quantifying uncertainties of estimated impacts (e.g. Masutomi et al., 2009; Garrido et al., 2011; Zhang et al., 2011; Islam et al., 2012; Osborne et al., 2013; Graux et al., 2013; Höglind et al., 2013; Deryng et al., 2014; Fuhrer et al., 2014). In addition, impact model uncertainties are increasingly considered through ensembles including multiple crop model parameterizations and/or multiple impact models (e.g. Aggarwal and Mall, 2002; Challinor et al., 2005; Tao et al., 2009; Semenov and Stratonovitch, 2010; Ceglar and Kajfez-Bogataj, 2012; Tao and Zhang, 2013; Asseng et al., 2013). Recent ensemble studies showed that variation among crop models can have large effects on uncertainty in estimated climate change impacts (Asseng et al., 2013; Bassu et al., 2014). In fact, variation among crop models (i.e. structural impact model uncertainty) can contribute even more to uncertainty than variation among downscaled GCMs (Asseng et al., 2013).

Such structural impact model uncertainty has only been quantified so far in mechanistic crop model ensembles where it is represented by variation in the description of functional relationships and parameter values. As an alternative approach, statistical crop models have been used to assess impacts of climate change on crop yields (e.g. Lobell et al., 2006; Iglesias et al., 2010; Schlenker and Lobell, 2010). Few ensembles have been run with statistical crop models using replicates of statistical models based on bootstrap resampling (e.g. Lobell et al., 2006; Tebaldi and Lobell, 2008). However, agro-climate ensembles involving different crop modelling approaches have never been applied so far.

In this study, for the first time three fundamentally different modelling approaches are applied in an impact assessment ensemble: a statistical crop model, a process-based crop model and a recently developed hybrid approach for estimating climate

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suitability of grain maize based on expert knowledge and observational data (Holzkämper et al., 2013). Climate suitability approaches were traditionally applied for regional assessments of preferential cultivation zones, but are also increasingly being applied for climate impact assessments (e.g. Hood et al., 2006; Daccache et al., 2012; Bradley et al., 2012; Diffenbaugh and Scherer, 2013; Ramirez-Villegas et al., 2013). Since yield data were used to refine the climate suitability evaluation in Holzkämper et al. (2013), climate suitability estimates could be translated into yield estimates, which makes them comparable to estimates derived with both the statistical and the process-based model in this study.

The three approaches differ conceptually and in their complexity. The process-based model simulates crop growth dynamically on a daily time-scale based on mechanistic process descriptions. The statistical model is static and hypothesizes causal relationships between temporally aggregated explanatory variables (i.e. yield predictors) and a response variable (i.e. yield) in a dataset (Holzkämper et al., 2012). The hybrid approach simulates phenological development dynamically and derives climate suitability estimates based on climatic predictor variables aggregated over different phenological phases. The relationship between climatic predictors and yield are thereby pre-defined based on information from literature and expert knowledge and subsequently refined within pre-defined bounds based on empirical data. All three modelling approaches have commonalities in that they include specific assumptions about crop physiological processes in the form of mechanistic equations (in the process-based crop model), selection of predictor variables and terms (in the statistical model), or pre-defined response functions (in the hybrid climate suitability approach). Furthermore, all three approaches also incorporate empirical elements to different degrees: Model coefficients or specific parameters are calibrated based on observed yield data. The process-based model includes a large number of physical parameters that cannot be known with certainty and therefore require calibration within realistic bounds. Similarly, the hybrid climate suitability approach requires the fitting of parameters within pre-defined bounds. The statistical model involves the greatest empirical component as it requires the fitting of model coefficients for the selected variables and terms without any boundary constraints.

The three approaches were used to quantify changes in yield potentials and in climatic limitations for different climate projections for grain maize in Switzerland. The aim was to assess implications of the choice of modelling approach for impact estimates by comparing results derived with the three approaches. For each approach, impact uncertainties due to model parameter and climate model uncertainty originating from climate model chain and downscaling approach were accounted for. Finally, the consistency of estimated changes in yield potentials and in climatic limitations was investigated, and strengths and weaknesses of each approach for climate impact studies are discussed.

2. Data

2.1. Observed climate and yield data

This study was conducted for three sites located in different climatic regions in Switzerland (Fig. 1). Magadino (MAG), located south of the Alps, is the wettest station with an annual average precipitation of 1832 mm and an average annual temperature of 11.4 °C. Payerne (PAY) in Western Switzerland is comparatively dry (891 mm) and cool (9.4 °C). Wädenswil (WAE) in the North-East is located in a region with a more balanced climate with 1390 mm mean annual precipitation and 9.5 °C average annual temperature.

Observed weather data at daily resolution was available for 65 automatic stations operated by the Swiss Federal Office of Meteorology and Climatology (MeteoSwiss). Grain maize yield data used for calibrating and fitting the models were derived from the Farm Accountancy Data Network of Switzerland (FAT, 2003). To relate weather data to yield data, records of the latter were aggregated within a 10-km radius around each weather station. Averages of all yields recorded within this radius for a particular year were matched with climate data of this station and year. Average yield levels estimated over the time period 1981–2009 for Switzerland was around 8.7 t/ha.

2.2. Climate projections

Climate projections were derived from 4 GCM-RCM model chains selected from the ENSEMBLES project database (http://www.ensembles-eu.org): ETHZ-CLM, KNMI-RACMO2, SMHIRCA-BCM, and SMHIRCA-HadCM. The scenarios feature combinations of 4 GCMs and 3 RCMs, all ran transiently with atmospheric composition specified by the IPCC A1B emission scenario. Two 30-year time windows were selected to represent current (1981–2010) and the near-future (2035–2064) climatic conditions. Given the choice of a relatively close future time period it was sufficient to consider a single emission scenario, as differences in climate projections due to different specifications of the greenhouse gas abundances are still small at this time horizon.

Two different statistical weather generators (UKCP09 and LARS-WG) were used to downscale the climate projections for the three study sites.

The UKCP09 stochastic weather generator (Kilsby et al., 2007) is built around the Neyman-Scott rectangular pulses (NSRP) model (Rodriguez-Iturbe et al., 1987; Cowpertwait et al., 1996). The NSRP model is used to generate hourly precipitation data, while simple, first-order autoregressive models are used to produce daily values of mean, minimum and maximum air temperature, vapour pressure, sunshine duration, global radiation, and wind speed. Training of the NSRP model with observed precipitation data was accomplished as described in Fatichi et al. (2011a, 2011b). The first-order autoregressive coefficients for the other weather variables were calibrated for half-monthly periods conditionally on the transitions between wet (W) and dry (D) days. There were altogether 4 + 1 transition types: WW, WD, DW, DD (Kilsby et al., 2007) with the additions of DDD, which was introduced in the 2011 version of UKCP09 by Jones et al. (2011) to better simulate long-lasting droughts.

LARS-WG (Semenov, 2007; Semenov and Barrow, 1997; Semenov and Stratonovitch, 2010) is a stochastic weather generator operating at the local scale and the daily time step that employs the serial approach proposed by Racsko et al. (1991) to model wet and dry series. Semi-empirical distributions and cross correlation matrices conditional on the wet/dry status of a day are specified to model rainfall amounts, daily minimum and maximum temperature and solar radiation (Semenov, 2007). Generating parameters are specified separately for each month of the year, with weighted interpolation between months applied to obtain a smooth seasonal cycle of the generating parameters (Semenov and Stratonovitch, 2010).

Both generators were trained with observed weather data for 1981–2010. Generating parameters for the future time window were obtained in both cases by applying climate change factors. The procedure adopted for the UKCP9 weather generator is the same as described by Kilsby et al. (2007). Concerning LARS-WG, the integration of the ENSEMBLES projections closely followed the steps detailed in Calanca and Semenov (2013). For generating daily data, temperature, rainfall and solar radiation are adjusted to account for changes in the duration of wet and dry spells (Semenov, 2007).