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Short Communication

Adjusting climate model bias for agricultural impact assessment: How to cut the mustard

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1. Introduction: crop-growth models, climate models, and bias adjustment methods

The growing conditions and key plant physiological processes of the most important staple crops for the human and animal food chains depend on climate conditions and are affected by climate extremes such as heat stress and drought (e.g. Porter and Semenov 2005; Lobell et al., 2014; Zampieri et al., 2017a). They will therefore be highly influenced by climate change in the coming decades (i.e. Rosenzweig et al., 2014; Iizumi et al., 2017).

The effects of climate change on crops can be estimated by using process-based crop models. Based on formulations of the essential physiological plant-growth processes (Zampieri et al., 2017b), they are used for both operational seasonal prediction of crop yields (i.e. MARS Crop Yield Forecasting System) and assessing climate-change impacts and adaptation measures for food production (Asseng et al., 2014; Rosenzweig et al., 2014; Caubel et al., 2015, 2016). For the latter, crop models rely on multi-decadal climate projections computed by global/regional climate models, e.g. in the framework of the Climate Model Intercomparison Projects (CMIP), or within regional initiatives such as the Coordinated Regional Climate Downscaling Experiment (CORDEX).

It is well known that climate model simulations are affected by both systematic and random errors, which prevent them from correctly simulating the occurrence and the intensity of extreme events such as droughts, heat waves, and extreme precipitation. *Model bias* normally refers to only one component of the error, i.e. the average difference between the modelled and observed values (e.g. glossary in climate4impact, Potempski and Galmarini, 2009). In climate science, however, the term has a broader meaning and it is used to represent the systematic errors (mean and higher moments) of a given variable (Teutschbein and Seibert, 2013; e.g. Liu et al., 2014; Maraun, 2016; Maraun and Widmann, 2018). Prior to using climate model simulations for (among many other applications) crop modeling, an *adjustment* of the variables is required so that their statistical properties are more similar to the ones observed. *Bias-correction,* or more properly *adjustment* (B-A) methods, developed as generic statistical techniques, have also been devised in large varieties for climate applications.

Even in the presence of the perfect uncertainty-free crop model (which is hardly the case, unfortunately), the adjustment of the climate data would not lead to improved usability. In fact B-A techniques are frequently applied *independently* on one or few variables thus constituting a serious burden for crop models which are based on highly non-linear formulations and therefore are particularly sensitive to variable inconsistencies that would lead to non realistic solutions.

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2. One workshop, four questions

In May 2017 a workshop was organized at the European Commission Joint Research Centre, in Ispra, Italy, to discuss the role and effect of climate data B-A on crop models as introduced above. The discussion developed around four crucial research questions:

Q1: What is the impact on crop models of independent B-As of coupled variables?

Q2: What can B-A offer to suit crop models specifically?

Q3: What can B-A not solve?

Q4: What next?

The result of the discussion and possible answers to the questions are presented hereafter. The latter may not be definitive or generally agreed upon but yet they can be the stimuli for a more general discussion within the widespread community of climate scientists, agricultural modelers and statisticians. Each of the next four section titles addresses a question and includes a synthetic answer to it.

3. Q1: What is the impact on crop models of independent B-As of coupled variables? A sensitivity yet to be quantified.

The susceptibility of crops to unfavorable weather conditions and extreme events during the growing season is very well known (e.g. Lobell et al., 2011; Lesk et al., 2016). Crop models typically require data on soil, crop characteristics, daily (or sub-daily) precipitation, downwelling short- and long-wave radiation, air temperature, relative humidity/partial water vapor pressure, wind speed (e.g. Zampieri et al., 2017a; Ewert et al., 2015; Boote et al., 2013), and information on crop management. Errors in the mean, extreme values, and time variability of climate parameters greatly affect crop models regardless of the spatial resolution of RCMs or dynamical downscaling of GCMs.

An example of the effect of independent adjustment of variables is presented in Fig. 1, where the observed, biased, and bias-adjusted values of Heat-Degree-Days (HDD), defined as the time integral of temperatures above 30 °C during the summer period, vs precipitation in Romania are shown. The univariate B-A (Dosio, 2016) slightly corrects the offset of the simulation from the observation, while the decoupled treatment of the variable produces an almost constant reduction throughout the precipitation range. Precipitation and temperature are key factors for crop growth (Ceglar et al., 2018) and one can expect important consequences when these data are used within a crop model. Similar problems may arise when direct radiation affecting the plant growth and correspondingly the air temperature, or soil moisture and precipitation are not adjusted jointly.

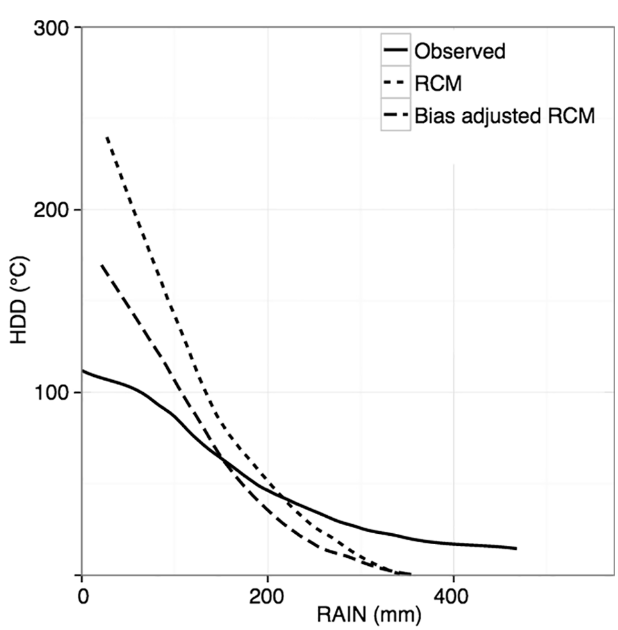

Fig. 1. Loess-fit of observed and simulated summer HDD and Precipitation. HDD is defined as the time integral of temperatures over 30 °C. RCA4 regional climate model, driven by MPI-M-MPI-ESM-LR GCM, provided data over the period between 1981 and 2010.

Alongside the bias adjustment of coupled variables, another critical and very relevant point in relation to climate and crop models was raised during the discussion. It relates to the capacity of the climate models to capture large-scale weather features and extremes and their effects during different phases of the crop growth (Casanueva et al., 2014; Ceglar et al., 2017; Zampieri et al., 2017a). In fact, capturing the conditions preceding and during the growing season plays a role in surface-related processes like soil moisture. Summer heat waves in Europe, for example, were shown to be often preceded by dry springs (Zampieri et al., 2009; Mueller and Seneviratne, 2012; Prodhomme et al., 2016) which affect crop yields (Ceglar et al., 2018). This issue was outlined as relevant to B-A for agricultural applications and in many cases an issue to be addressed prior to B-A of climate data (see Section 5).

Although several studies have been performed in the past to determine the importance of B-A in crop modeling (e.g. Liu et al., 2014; Hawkins et al., 2013; Ceglar and Kajfež-Bogataj, 2012), few efforts have systematically assessed the existing B-A methods and the impact of the treatments of the data on crop models. The need to systematically and quantitatively estimate the impact of these two issues on crop models has therefore been recognized and acknowledged, as well as the need to organize community activities involving statisticians, climate modelers, and crop modelers to address them.

4. Q2: What can B-A offer to suit crop models specifically? Classification and characterization of B-A methods

Having identified B-A of coupled variables as a potentially important issue for agricultural use of climate model results, the workshop provided an opportunity to survey the existing B-A methodologies and categorize them in relation to agricultural applications.

Bias-adjustment of climate variables for crop modeling has a multidimensional character that can be treated in different ways, namely:

- *Multi-variable B-A*: in addition to adjusting the marginal distribution of each variable, the dependencies between variables can also be adjusted.
- *Multi-site B-A*: climate variables are often needed at multiple locations; one could therefore correct not only the marginal distributions of a variable at the various sites, but also the spatial (inter-site) dependence structure.
- *Multi-variable and multi-site B-A*: in addition to correcting both the spatial and inter-variable dependency structures, the *cross-dependencies* of a variable at different locations could also be corrected.

For crop model applications one may also need to include temporal dependencies in the adjustment, whether in univariate B-A (Johnson and Sharma, 2012), a multi-site B-A (Mehrotra and Sharma, 2015), or a multi-variable B-A (Mehrotra and Sharma, 2016). Most of the B-A methods currently used work in a univariate context, wherein the distribution of a univariate time series at a single spatial location is adjusted independently from every other variable and location. Recently a few multivariate methodologies have been proposed and applied to climate model data (e.g., Bardossy and Pegram, 2012; Piani and Haerter, 2012; Mao et al., 2015; Vrac and Friederichs, 2015; Cannon, 2016, 2018; Dekens et al., 2017; Li et al., 2017; Vrac, 2018). The increased detail in treating multiple variables and locations by any multivariate B-A method can modify the temporal sequencing and properties of the adjusted data and, depending on the method, may produce a loss of coherence with the driving climate model or observations.

In the remainder of this section we provide a brief overview of the most relevant methodologies as they were presented at the workshop so that one can appreciate the spectrum of the different approaches and how they fit in the general categories listed above. Unless specified otherwise, these methods are applied to multiple locations independently, and use a monthly, seasonal, or moving-window approach to handle seasonality.

The *Parametric quantile-quantile mapping* (*PQ-QM*) is a univariate method based on the calculation of a transfer function (TF) such that the marginal cumulative distribution function (CDF) of the adjusted variable matches the observed one. The TF is usually estimated as a function of up to four parameters for precipitation, and linearly for temperature (Piani and Haerter, 2012; Dosio and Paruolo, 2011). It has been applied to projections of mean and extreme climate variables over Europe and used for climate change impact assessment (Dosio et al., 2012; Ruiz-Ramos et al., 2016; Dosio and Fischer, 2018).

The *Kernel Density Distribution Mapping* (KDDM, McGinnis, et al., 2015) operates similarly to PQ-QM. It adjusts data values by transforming them into probabilities according to the model output CDF, then transforming those probabilities back into data values using the observed-data inverse CDF. PQ-QM constructs its TF by fitting parametric distributions to the datasets and composing closed-form expressions for the corresponding CDFs; KDDM estimates the probability density functions (PDFs) of the datasets non-parametrically, integrates them to get CDFs, and constructs a TF by fitting a spline to corresponding CDF quantiles (details in McGinnis, et al., 2015).

A variant of the empirical quantile-mapping method is the *CDF-t technique* (Vrac et al., 2012). It first estimates the CDFs of "pseudo" reference data over the projection time period (either future or evaluation time period) before applying a distribution-derived quantile-mapping between the CDF of the model simulations and that of pseudo-references, both for the projection period. Then, based on this estimation and on the projection model data CDF, a distribution-based quantile mapping is performed. This places the B-A within the appropriate time period. CDF-t then performs a quantile-mapping technique based on the CDFs over the projection time period and therefore accounts for changes of CDF within the calibration period. CDF-t has been already applied to feed crop models (Oettli et al., 2011) and for various other applications (e.g., Lavaysse et al., 2012; Vautard et al, 2013; Vigaud et al., 2013). A version was also designed specifically for extreme events (Kallache et al., 2011).

Another parametric version of the QQ mapping developed at the Swedish Meteorological and Hydrological Institute (SMHI) for climate simulations in hydrological applications is the *Distribution-Based Scaling* (*DBS*, Yang et al., 2010). DBS adjusts precipitation and other extremes separately from the rest of the distribution, and temperatures conditionally on the adjusted precipitation. Conditional correction of temperatures is a step towards bias adjustment of multiple variables, for example as introduced by the final two general purpose multivariate methods.

The *N-dimensional Multivariate Bias Correction* (MBCn; Cannon, 2018) is a form of multivariate quantile mapping that is based on an image processing technique proposed by Pitié (2005, 2007). MBCn adjusts the simulated dependence structures to match observations while modifying the temporal sequencing of the climate simulations enough to match the observed multivariate distribution. This is achieved by iteratively applying a random orthogonal rotation to the datasets followed by univariate-quantile-mapping of the rotated marginal distributions. Multi-sites and multi-variables can be adjusted simultaneously. A caveat is that loss of temporal coherence with the climate simulations becomes larger as the number of dimensions increases. MBCn has been applied in event attribution studies of extreme fire weather risk in western Canada (Kirchmeier-Young et al., 2017, 2018).

The *Rank-Resampling for Distributions and Dependencies* (*R2D2*, Vrac, 2018) is a multivariate B-A procedure working with multi-sites and variables. R2D2 adjusts the univariate marginal distributions and the dependence structures separately based on a rank resampling algorithm. R2D2 introduces stochasticity by iterating across all possible dimensions and generating as many multivariate adjustments as the number of statistical dimensions of the simulations to be corrected. The rank-dependence-stationarity assumption allows treating several thousands of statistical dimensions and reconstructing spatial and inter-variable structures.

It is clear that although these techniques are all variants of classical methods, they are not expected to give identical results because the assumptions, the approaches, and the data treatments are all different. It is therefore important to compare the various methods when applied to a common case, and most importantly, to evaluate the effect of uni- vs multi-variate methods on crop models. These and other methods are part of the activity organized as main result of the workshop as described in Section 6.

5. Q3: What can B-A not solve? B-A is not a *panacea*!

The issues presented in Section 2 in relation to the simulation of large-scale climate features and their relevance to agricultural modelling application were expanded when discussing the limits of B-A. The following considerations were brought forward and a suggestion presented.

B-A does not correct for models' deficiencies in representing fundamental physical processes (Dosio, 2016; Stocker et al., 2015; Maraun et al., 2017). Furthermore, the attempt to bias-adjust and remove large errors may not only fail, but introduce severe new artefacts (Maraun et al., 2017). For instance, a climate model may under-represent the occurrence and duration of very long dry spells. In some cases, e.g. when the climate model does not resolve the particular orographic shielding of a valley from rain, B-A may indeed be successful. But if the model's planetary scale dynamics produces a too weak persistence of blocking highs, B-A will not remove the problem. Further, even if a wet-day adjustment corrects the overall wet-day frequency, the resulting spell distribution might be further distorted.

For a successful B-A, a climate model has to represent the relevant climatic processes sufficiently well in the first place. Any bias adjustment should therefore be preceded by a careful evaluation of the relevant process representation by the model to be used, and a careful selection of the climate models to adjust (Maraun et al., 2017). As it is evident that a model that fundamentally misrepresents the ENSO dynamics should not be used to assess rainfall changes over Peru, it should also be evident that caution should be applied when using and B-A data from models that fail in representing key large-scale climatic processes. An additional relevant issue is the quality and temporal coverage of the observational reference data series, which will not be tackled here.

At this stage, it is therefore clear that a well-defined model evaluation protocol is needed that identifies the climatic features whose representation within the simulation must be checked and determines their occurrence, interactions, and impacts on the data to be bias-adjusted. Such a protocol should be specific for the subsequent use of the climate model data in impact models and therefore should be *fit-for-purpose* (Steyn and Galmarini, 2008).

6. Q4: What next? From words to action – DECIFER and BAD-JAM

All the considerations presented above point toward:

1. Designing tailor-made activities finalized at the definition and application of climate model evaluation protocols and practices.
2. Determining the sensitivity of crop models to B-A techniques and identifying those most suited for the treatment of climate predictions and projections for agricultural model applications.

Toward these ends, two activities were proposed at the workshop:

DECIFER and *BAD-JAM*, the latter being already in progress**.**

DECIFER (*Distilling Ensemble Climate Information for Food sEcuRity*) aims at deriving robust information on agricultural impacts of climate change and extremes in the Greater Mediterranean region. Specifically, it aims at understanding how climate model quality affects B-A and subsequent crop model simulations. Such an activity will develop over a number of years. It is presently in search of financial support, as it will involve a great deal of scientific research and the development of sound protocols and procedures for model evaluation and selection.

Within BAD-JAM (*Bias ADJustment for Agricultural Models*), started in Fall 2017, a community of climate modelers and statisticians (authoring this article) has used 13 B-A methods (variations of the methods described in Section 3.) to produce B-A time series of 7 agro-relevant variables from 8 EURO-Cordex models at 21 locations across Europe and Northern Africa from 1980 to 2100. Historic data were adjusted for the evaluation period 1980–1985 based on the training period 1985–2005. The B-A was thereafter applied to the projections for 2006–2100. The adjusted climate data are being analyzed at the Joint Research Centre and are also being made available to 32 members of the AgMIP-wheat modeling community (Asseng et al., 2014) who will use them to determine wheat-yield-related variables. The results will then be inter-compared and critically analyzed in the light of the B-A technique used (i.e. uni- vs multi-variate) and the differences in the climate data used. The number of methods, climate model sets, and crop models applied at the designated locations (~70,000 data sets) is expected to provide good statistics and a good overview of the sensitivity of crop models to B-A techniques. Subsequent publications will detail the results of this ongoing activity.

In a second phase, BAD-JAM will be extended to gridded data to address the multi-location dimension of the adjustment and B-A will be performed only on model sets identified by DECIFER as *fit-for-purpose*.

7. Conclusions

The relevance of the agricultural sector in sustaining society, as well as the threats presented by climate change, require cautious use of modelling systems and the possibility of controlling the quality of the modelling chains at each step. The verification of the quality of the different components that lead to an impact assessment is of paramount importance when the assessment is used as a tool for policy or decision making (Solazzo et al., 2018). That is the case of climate model projections used to for agricultural impact assessments. Bias-adjustment of climate model data requires credible simulations and will have to produce self consistent adjustment of variables given the high sensitivity of crop models to input data. A survey of the problem and the proposed activities in an attempt to improve the quality of the modeling chain have been presented and are currently being carried out as results of a workshop held in 2017.

Conflict of interest

None.

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Further reading

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