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Assessing uncertainty and complexity in regional-scale crop model simulations

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ABSTRACT

Crop models are imperfect approximations to real world interactions between biotic and abiotic factors. In some situations, the uncertainties associated with choices in model structure, model inputs and parameters can exceed the spatiotemporal variability of simulated yields, thus limiting predictability. For Indian groundnut, we used the General Large Area Model for annual crops (GLAM) with an existing framework to decompose uncertainty, to first understand how skill changes with added model complexity, and then to determine the relevant uncertainty sources in yield and other prognostic variables (total biomass, leaf area index and harvest index). We developed an ensemble of simulations by perturbing GLAM parameters using two different input meteorology datasets, and two model versions that differ in the complexity with which they account for assimilation. We found that added complexity improved model skill, as measured by changes in the root mean squared error (RMSE), by 5–10% in specific pockets of western, central and southern India, but that 85% of the groundnut growing area either did not show improved skill or showed decreased skill from such added complexity. Thus, adding complexity or using overly complex models at regional or global scales should be exercised with caution. Uncertainty analysis indicated that, in situations where soil and air moisture dynamics are the major determinants of productivity, predictability in yield is high. Where uncertainty for yield is high, the choice of weather input data was found critical for reducing uncertainty. However, for other prognostic variables (including leaf area index, total biomass and the harvest index) parametric uncertainty was generally the most important source, with a contribution of up to 90% in some cases, suggesting that regional-scale data additional to yield to constrain model parameters is needed. Our study provides further evidence that regional-scale studies should explicitly quantify multiple uncertainty sources.

1. Introduction

Crop models are imperfect approximations to real world interactions between biotic and abiotic factors, mainly designed as tools that provide information that is useful for farmers, researchers and policy makers (Affholder et al., 2012; Sinclair and Seligman, 1996). Such information allows making decisions regarding changes in cropping systems at different spatio-temporal scales, with varied degrees of confidence (Challinor et al., 2014). As confidence in crop modelling outcomes depends on the errors and uncertainties associated with the simulation of the system in question, adequately sampling the model and parameter spaces and adequately addressing issues related to data quality and scaling are critical for the delivery of robust information (Kennedy and O'Hagan, 2001; Ramirez-Villegas et al., 2015).

As with environmental models in general, uncertainty in crop modelling arises from the impossibility to model the system (i.e., the cropping system) with complete determinism (Walker et al., 2003). As a result of the ad-hoc nature of crop model development, where models are developed to fit a specific purpose (Affholder et al., 2012), large diversity exists in model structure and complexity (Rivington and Koo, 2011) and hence model structure is a key source of uncertainty (Asseng et al., 2014; Challinor et al., 2014). Lack of precision in parameter values is also an important uncertainty source in crop models. In many modelling applications, calibrated parameters are rarely sufficiently constrained by the available observational data, which is in most cases limited to

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crop yield and/or phenology (Iizumi et al., 2009), and this results in crop model parameterisations that are incomplete and uncertain (Angulo et al., 2013a). In some cases, parameters are inherited from other models or crops, are assigned values using expert judgment (Tubiello et al., 2007), or are left 'as default' [e.g., Jalota et al. (2013) and Lobell et al. (2013)].

Under a variety of situations, the errors and uncertainties associated with choices of crop model structure, parameters, and data sources can exceed the spatiotemporal variability of the system modelled, thus limiting its predictability, particularly when models are used beyond their calibration ranges (Koehler et al., 2013; Li et al., 2015; Montesino-San Martin et al., 2015). For example, variation in simulation dynamics due to varying model structure has been shown to increase as environmental conditions differ more from the observational record (Asseng et al., 2013; Bassu et al., 2014). Similarly, model parameters and model meteorological inputs have been shown to affect the accuracy of simulated yield across a range of conditions (Tao and Zhang, 2013; Van Bussel et al., 2011b). Choices in crop model structure or model configuration can also greatly affect the modelling outcomes that underpin decisions (Vermeulen et al., 2013; Weaver et al., 2013).

Remarkably, in spite of the emphasis on error and uncertainty quantification that has accompanied most recent developments in crop modelling (including the increased use of models outside their calibration ranges, e.g., as in climate change impact studies), still only a handful of studies assess multiple uncertainty sources and about one third appropriately address model error by conducting model evaluation [see Ramirez-Villegas et al. (2015) for a review on the topic]. Importantly, with the increased generation of spatially-explicit gridded crop model simulations, not accounting for parametric uncertainty and input data scaling may lead to systematic bias in estimated crop yield responses to temperature and precipitation (Challinor et al., 2015). Thereby, studies comparatively assessing uncertainties arising from model structure, model parameters and input data are warranted.

This work focuses on Indian groundnut and uses the General Large Area Model for annual crops (GLAM, Challinor et al., 2004) in combination with observed yield and weather data to investigate two key aspects of prediction: complexity and uncertainty. Specifically, we develop a parameter ensemble by perturbing 30 GLAM model parameters using two different input meteorology datasets, and two model versions that differ in the way they account for assimilation. We first analyse yield observations and simulations to determine whether and how skill improves across different regions depending on the different model structures (warranted complexity), and then decompose the variance of simulated historical yield and other model prognostic variables (LAI, biomass, harvest index) to determine the dominant uncertainty sources across the analysis domain. The results of this work contribute insights to enhance understanding of uncertainty in crop simulation at regional scales.

2. Materials and methods

2.1. Study region

The study area consisted of all $1 \times 1^{\circ}$ pixels (ca. 100×100 km at the Equator) of India where the average cultivated area of groundnut in the period 1966–1990 was greater than 0.2% (Challinor et al., 2003; Mehrotra, 2011). Following Talawar (2004), we classified all $1 \times 1^{\circ}$ pixels into one of five groundnut growing zones, which are known to reflect the variation in germplasm grown across India (Fig. 1). These regions receive different amounts of precipitation during the monsoon season (June–September, when groundnut is primarily grown) and have different prevalent soil types.

2.2. Input data

2.2.1. Weather data

Daily meteorological inputs required for GLAM are precipitation, downwards shortwave radiation flux and minimum and maximum temperatures. In this study, two sets of these four inputs were used to reflect uncertainty in the choice of input meteorology, as described below.

The first set (referred to as WTH-A) follows the original GLAM formulation of Challinor et al. (2004) and consists of observed daily precipitation data from the Centre for Climate Change Research (CCCR) of the Indian Institute for Tropical Meteorology (IITM) (Rajeevan et al., 2005). We downloaded precipitation data from the CCCR portal (http://cccr.tropmet.res.in/cccr/home/index.jsp, accessed 1st September 2011) at the native $1 \times 1^{\circ}$ resolution for the period 1961–2008 (IMD dataset, hereafter). The IMD dataset is based on the interpolation of daily rainfall data from 1803 rain gauges across India (Rajeevan et al., 2006, 2005). We obtained maximum and minimum monthly temperatures from the Climatic Research Unit (CRU) dataset at 0.5° (CRU-TS3.0 at http://www.cru.uea.ac.uk/cru/data/hrga, accessed 1st September 2011) (Mitchell and Jones, 2005). We first scaled the CRU data onto the $1 \times 1^{\circ}$ grid using area-weighted averages and then linearly interpolated to daily values using middle days of the months. Finally, we gathered daily total downwards shortwave solar radiation data from the open-access version of the European Centre for Medium-Range Weather Forecasts (ECMWF) 40+ Reanalysis (ERA-40) (Uppala et al., 2005), available at http://data-portal.ecmwf.int/data/d/era40_daily/ (accessed 1st September 2011) and then scaled it onto the $1 \times 1^{\circ}$ grid using nearest-neighbour interpolation.

The second set (referred to as WTH-B) is the Water and Global Change (WATCH) Forcing Dataset (WFD), fully described by Weedon et al. (2011). The WFD is a global sub-daily time-step gridded dataset at half-degree resolution for the period 1958–2001, developed by means of bias correction of the ERA-40 reanalysis. The dataset is of comparable quality to that of Sheffield et al. (2006), and is amongst the gridded datasets used in global and regional crop modelling frameworks (Elliott et al., 2014; Ruane et al., 2015). For a complete description and analysis of the dataset the reader is referred to Weedon et al. (2011, 2010). We downloaded daily data for total precipitation, downward shortwave radiation, and maximum and minimum temperatures from the WFD website (https://gateway.ceh.ac.uk/home, accessed 15th June 2013) and aggregated them to the study resolution ($1 \times 1^{\circ}$).

2.2.2. Soil data

Spatially variable values of permanent wilting point (θ_{ll}), field capacity (θ_{ul}) and saturation (θ_{sat}) moisture contents were derived from the 30 arc-sec Harmonized World Soil Database (HWSD) (Batjes, 2009; FAO, 2012). The spatially explicit properties in the soil classes occurring within the analysis domain were calculated as the area-weighted-average of each soil profile in each 1×1 grid cell of the analysis grid (see Fig. 1). This resulted in three (one for each soil moisture limit) spatially explicit continuous $1 \times 1^{\circ}$ datasets that covered the analysis domain. In each grid cell, a GLAM simulation was always associated with its three respective soil moisture content values.

2.2.3. Planting dates

Planting windows used here were those of the global study of Sacks et al. (2010). The dataset of Sacks et al. (2010) is the first global dataset with georeferenced crop planting and harvesting information. The data were aggregated onto the $1 \times 1^{\circ}$ analysis grid using area-weighted averages and carefully checked for inconsistencies to ensure planting windows followed the monsoon dynamics.