Europ. J. Agronomy xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

European Journal of Agronomy

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

Implications of climate model biases and downscaling on crop model simulated climate change impacts

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ARTICLE INFO

Article history:
Received 7 July 2015
Received in revised form 3 March 2016
Accepted 25 May 2016
Available online xxx

Keywords:
Climate model
Bias
Uncertainty
Downscaling
Bias correction
Crop simulation models
Barley

ABSTRACT

In estimating responses of crops to future climate realisations, it is necessary to understand and differentiate sources of uncertainty. This paper considers the specific aspect of input weather data quality from a Regional Climate Model (RCM) leading to differences in estimates made by three crop models. The availability of hindcast RCM estimates enables comparison of crop model outputs derived from observed and modelled weather data. Errors in estimating the past climate implies biases in future projections, and thus affect modelled crop responses. We investigate the complexities in using climate model projections representing different spatial scales within climate change impacts and adaptation studies. This is illustrated by simulating spring barley with three crop models run using site-specific observed (12 UK sites), original (50 × 50 km) and bias corrected downscaled (site-specific) hindcast (1960–1990) weather data from the HadRM3 RCM. Though the bias correction downscaling method improved the match between observed and hindcast data, this did not always translate into better matching of crop model estimates. At four sites the original HadRM3 data produced near identical mean simulated yield values as from the observed weather data, despite evaluated (observed-hindcast) differences. This is likely due to compensating errors in the input weather data and non-linearity in the crop models processes, making interpretation of results problematic. Understanding how biases in climate data manifest themselves in individual crop models gives greater confidence in the utility of the estimates produced using downscaled future climate projections and crop model ensembles. The results have implications on how future projections of climate change impacts are interpreted. Fundamentally, considerable care is required in determining the impact weather data sources have in climate change impact and adaptation studies, whether from individual models or ensembles.

1. Introduction

A key area of uncertainty in modelling the potential impacts of climate change (CC) on agro-ecosystems is the utility of data representing future weather projections. Such projections are often used within models of the soil-plant-atmosphere-management relationships (e.g. crop models) for CC impacts, mitigation and adaptation studies (Elliott et al., 2014; Rosenzweig et al., 2014).

Conventionally, the input of projected CC changes into crop models can be achieved through top-down methods which focus on developing fine-scale climate data from raw Global Climate Model data (Mearns et al., 1999; Challinor et al., 2005; Moriondo and Bindi, 2006) or via dynamical downscaling using Regional Climate Models (Murphy et al., 2009; Rötter et al., 2011). Conversion of projection data via a weather generator (Semenov and Barrow, 1997; Kilsby et al., 2007) or by applying climate change anomalies to observed time series (Tubiello et al., 2000) and bias correction methods (Rivington et al., 2008b; Themeβl et al., 2012; Teutschbein and Seibert, 2012; Wilcke et al., 2013) result in finer local-scale weather scenarios, which are fed into impact models.

Global Circulation Models (GCM) estimates are at too coarse a spatial scale to be utilised in site-specific studies (Jagtap and Jones, 2002). Regional Climate Models (RCM) estimates are better at representing finer spatial scales, but may inherit systematic and random errors from the parent GCM (Murphy et al., 2004, 2009). However, RCM outputs might not properly reflect events that are most relevant for crop growth and development, such as the magnitude and frequency of precipitation or temperature (Rivington et al., 2008a; Goodess, 2013). This is the reason why the modelled weather data are compared against observations prior to their use

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http://dx.doi.org/10.1016/j.eja.2016.05.012

Please cite this article in press as: Cammarano, D., et al., Implications of climate model biases and downscaling on crop model simulated climate change impacts. Eur. J. Agron. (2016), http://dx.doi.org/10.1016/j.eja.2016.05.012

(hindcast). When the hindcast can reasonably reproduce observed data, then the potential exists for meaningful adjustment using either statistical downscaling or bias correction (BC) methods.

Most climate models (GCM and RCM) have been evaluated for their abilities to represent the past weather at specific locations (Achberger et al., 2003; Bell et al., 2004; Fowler et al., 2005). Moriondo and Bindi (2006) concluded that for a single site (Florence, Italy) a GCM and RCM were not able to recreate the daily maximum temperature (T_{max}) and minimum temperature (T_{min}) patterns for most of the year. Rivington et al. (2008a) found that for a UK RCM based set of simulations the hindcast data included a considerable excess of small (<1 mm) precipitation events, resulting in the number of dry days being under-estimated by an average of 60%, estimates of T_{min} tended to be over-estimated by an average of about 1 °C and solar radiation data showed clear over-estimation systematic bias. The terms “error”, “bias” and “uncertainty” are often used interchangeably, causing confusion as they can mean very different things. We use “error” as a measure of the *difference* between past measurements and values simulated with a model, being random and/or systematic. Similarly “bias” is a function of accumulated (systematic) errors. Error and difference are thus inter-changeable terms. The aim of BC is to reduce bias by minimising individual data point errors (observed minus climate modelled differences). The imperfect representation of rainfall is one of the major factors affecting the use of such products in impact models (such as crop models) for estimating crop production in rainfed systems (Cammarano et al., 2013).

Crop simulation models integrate the effects of temporal and multiple stress interaction on crop growth under different environmental and management conditions (Basso et al., 2001). Many crop model studies of responses to future climates use either data directly from climate models (single models or ensembles), potentially giving a misrepresentation of spatial scale, or data from weather generators or other approaches to downscaling. There is a need to address how errors in any of these sources affect crop model estimates (Challinor et al., 2005). Asseng et al. (2013) found that a significant proportion of the uncertainty in CC impact projections was mostly ascribed to variations among crop models rather than to variations among downscaled GCMs. However, the aim of their study was not to understand how biases in the input hindcast data manifest themselves within crop simulation models, and subsequently how errors may arise when using future projection data.

Previous studies have sought to quantify the impact of weather data utility on crop model estimates (i.e. Nonhebel 1994; Aggarwal 1995; Rivington et al., 2006). However, to date the use of a multi-crop model approach has not been used to quantify the relationship and error manifestations between weather data type, weather source, and multiple crop models. Without some understanding of how these errors manifest themselves in multiple crop model estimates, the utility of impact studies might be reduced by potentially producing misleading results.

The aim of this study was to illustrate the consequences of using different weather data sources on future crop production estimates without adequate evaluation of data utility and impacts on crop model simulations. The objectives of the study were: (i) to investigate how differences in the use of weather data products manifest themselves as errors in simulated outputs made by three crop models; (ii) to study the range and magnitude between observed and modelled weather data; (iii) investigate the consequences of application of bias correction method (BC) to future projection data and use in the crop models (Note: this makes estimates of future crop responses, but is not specifically an impacts study, as there are other considerations required).

2. Materials and methods

2.1. Climate data source

The British Atmospheric Data Centre (BADC, 2006) provided observed daily data (ObWT) for precipitation (mm), maximum and minimum temperature (T_{max} and T_{min}, °C) and total downward surface shortwave flux (sum of direct and diffuse solar radiation) S_o (MJ m^2 day^{-1}) for the period 1960–1990 at 12 meteorological stations in the UK (Fig. 1). Sites were selected based on the completeness of their meteorological data record and geographical suitability for crop production. Three sites (Inverness, Bush and Galashiels) did not have observed S_o. Instead, S_o was estimated at the first two sites using the Campbell-Donatelli model based on air temperature (Donatelli and Campbell, 1998), which proved appropriate for UK in the absence of sunshine duration inputs (Rivington et al., 2005). At Galashiels, where observed sunshine duration was available, S_o was estimated using the Johnson-Woodward model (see Rivington et al., 2005). Observed data were compiled within an Oracle database, where errors, duplicates and anomalies in the data were identified and corrected. A small number of missing observed values were estimated using a search and optimisation method (LADSS, 2012). Site elevation, latitude and longitude were included in the weather data as they were used as inputs to the crop simulation models.

The Hadley Centre, via the BADC, provided modelled data from the HadRM3 RCM archive for 50 × 50 km grid cells (Fig. 1). As an initial condition ensemble, five hindcast simulations (starting from 1860) were produced by the HadRM3 in order to establish 1960–1990 climate normal period ‘baselines’ to be used for comparisons with future projections. These hindcast simulations varied slightly in their initialisation conditions, but atmospheric carbon dioxide (CO_2) and other greenhouse gas (GHG) concentrations were varied to match the historical concentrations up until 1990. Future projections of GHG, as per the Special Report on Emissions Scenarios (SRES) (Nakocenovic and Swart, 2000) were not applied within the RCM until after 1990. One site, Auchincruive, was on the boundary between two RCM cells. Initial tests showed the cell containing large areas of sea (4693) had larger differences compared to the observed data than the neighbouring cell (4694 with 100% land surface), hence cell 4694 was used.

This data set, whilst superseded by more recent ensemble-based RCM estimates, provides a suitable single model case example with which to demonstrate the methodological approach used here. Use of RCM ensemble data (i.e. Murphy et al., 2009), whilst desirable as an approach to address climate uncertainty in specific impacts modelling work, would make for excessively complicated analysis and difficulties of diagnosis of error manifestation in the crop model estimates in this study.

Five weather data sets were used: (i) observed weather data (ObWT); (ii) the HadRM3 initial realisation original hindcast for 1960–1990 (Original Hindcast, OrH); (iii) the OrH data downscaled using the bias correction (BC) method of Rivington et al. (2008b) (Downscaled hindcast, DsH); the HadRM3 estimates for the SRES A2 (medium-high GHG emissions) original future projections for 2070–2100 (Original Future Projection, OrF); (iv) the OrF data downscaled using the BC method (Downscaled Future projection, DsF).

This paper uses a single example of the hindcast configurations of the HadRM3, and one CC scenario (A2 medium-high GHG emissions for the period 2070–2100). This is in recognition that any given emission scenario could produce different future climate projections at the regional scale. Hence this study is not an impacts one specifically (as there are many other issues required to be addressed such as combined water, temperature and CO_2 responses and

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