European Journal of Agronomy 90 (2017) 1–11

Contents lists available at ScienceDirect

European Journal of Agronomy

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

Modelling fertiliser significance in three major crops

Ben Parkes[a,*], Benjamin Sultan[a], Philippe Ciais[b], Xuhui Wang[b,c]

[a] Sorbonne Universités (UPMC, Univ. Paris 06)-CNRS-IRD-MNHN LOCEAN/IPSL, 4 Place Jussieu, F-75005 Paris, France
[b] Laboratorie des Sciences du Climat et de l'Environnement, Commissariat a L'Energie Atomique, 91191 Gif sur Yvette, France
[c] Laboratoire de mtorologie dynamique, Université Pierre et Marie Curie, 4 Place Jussieu, F-75005 Paris, France

ARTICLE INFO

Keywords:
Fertiliser
Statistical modelling
Maize
Rice
Wheat

ABSTRACT

We present work using two long-term climate datasets to show that nitrogen fertiliser is an important aspect of yield projection for three major crops. The ability of linear models using climate variables as predictors to accurately project the yield of maize, rice and wheat over multi-decadal scales is improved with the addition of fertiliser as an input.

Highly productive nations including Argentina, India, Poland and South Africa show significant improvement in yield simulations and show that fertiliser use should not be discounted when estimating yield variability. The use of nitrogen fertiliser in the generalised linear models improves yield forecast by 18% using the Princeton climate dataset and 23% using the WFDEI climate dataset. This work therefore supports the use of additional predictors than climate for improving the ability of statistical models to reconstruct yield variability.

1. Introduction

Statistical models have been used in a number of studies to identify contributing factors or project crop yields. Statistical models have been used at sub-country and country scales (Estes et al., 2013; Hernandez-Barrera et al., 2016; Wang et al., 2014; Zhou and Wang, 2015) in addition to continental (Iglesias et al., 2012) and global simulations (Lobell and Burke, 2010). They have also been used to for analysis of the role of different drivers controlling yield variability and trend of various crops including maize (Estes et al., 2013; Iglesias et al., 2012; Lobell and Burke, 2010; Zhou and Wang, 2015), rice (Wang et al., 2016; Zhou and Wang, 2015) and wheat (Estes et al., 2013; Hernandez-Barrera et al., 2016). Further detailed reviews of the use of statistical models include Boote et al. (2013), Shi et al. (2013) and White et al. (2011).

The alternative to using a statistical model is to use a process based model which simulates the growth and development of the crop. Detailed descriptions of process based models are found in the model description papers and examples include APSIM (Keating et al., 2003), LPJmL (Bondeau et al., 2007), ORCHIDEE-Crop (Wu et al., 2016) and STICS (Brisson et al., 2003) among many others. The Agricultural Model Intercomparison Project (AgMIP) has performed comparisons between multiple process based models and has shown the benefits of working with many models (Martre et al., 2015; Müller et al., 2017).

Many statistical models of crop yield rely on the assumption that the interannual variability (IAV) of yield is driven entirely by climate, here we investigate to what extent the contribution of fertilizer use modulates climate driven yield IAV (Shi et al., 2013). The different amount of fertiliser could partly explain why two regions of the same climate, experience a difference in yield and yield variability. The addition of fertiliser as an input into simple statistical models may also explain more of the variability in current yields which is important if statistical models are to be used for future projections.

Comparisons of statistical and process based models have arrived at several conclusions. With the lower complexity of statistical models they are generally much quicker than the process based counterparts. Statistical models are suitable for linking yield to yield influencing factors, however when outside of their training range their reliability is weakened (Gornott and Wechsung, 2016). Statistical models using data close to their training range are suitable for use in making projections (Lobell and Asseng, 2017).

The use of climate only drivers in statistical models of crop yield means that projections made by these models do not take into account the change in use of fertiliser. Fertiliser use is an important component of past yield trends and as the yield gap is still partly attributed to insufficient fertiliser input in some regions, fertilisers are therefore a key driver of future yield trends. Statistical models have been used with nitrogenous fertiliser in previous studies including Iglesias et al. (2012). In addition Mueller et al. (2012) has found that maize, rice and wheat are nutrient limited in several regions which therefore indicates that information on nitrogen fertiliser is important. The variability of the climate contributes strongly to the yield variability, fertiliser usage

* Corresponding author.
E-mail address: ben.parkes@locean-ipsl.upmc.fr (B. Parkes).

http://dx.doi.org/10.1016/j.eja.2017.06.012
Received 17 February 2016; Received in revised form 28 June 2017; Accepted 30 June 2017
1161-0301/ © 2017 Elsevier B.V. All rights reserved.

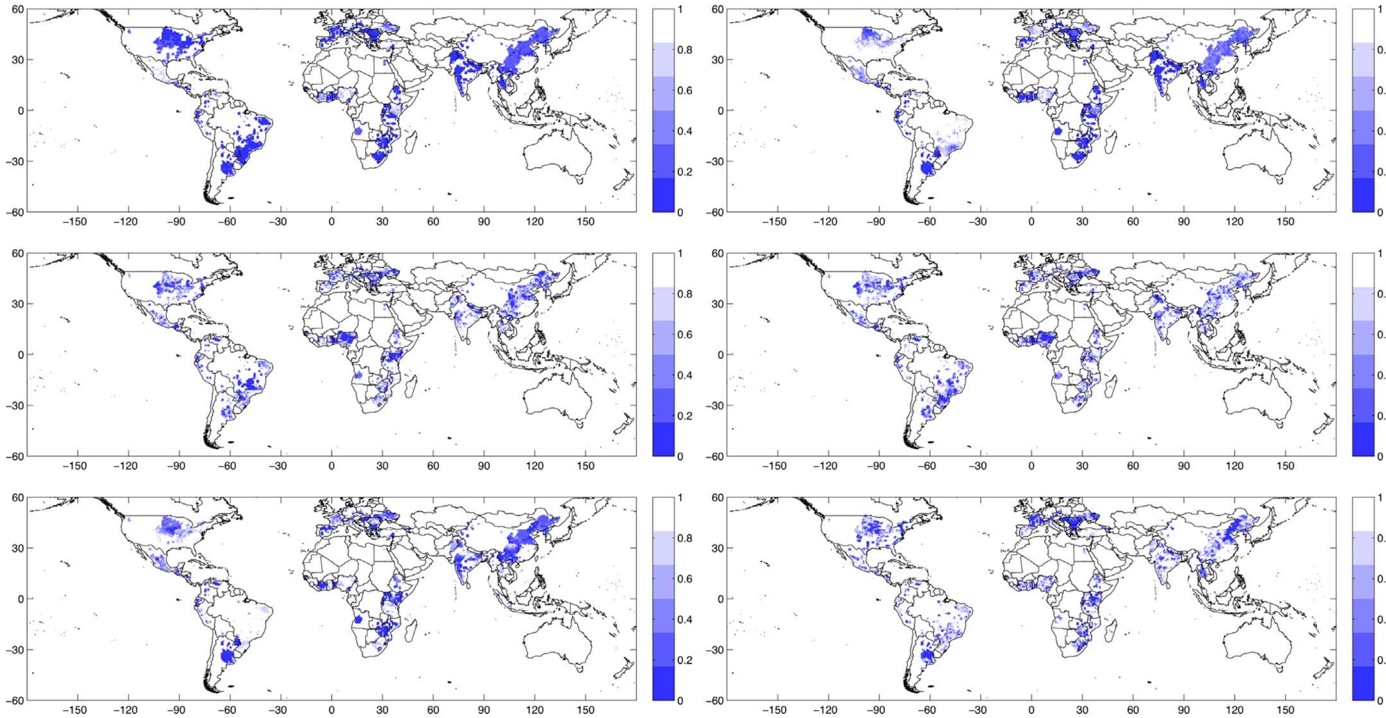

Fig. 1. Significance values for models for climate only (left) and climate and fertiliser (right) for maize (top), rice (middle) and wheat (bottom) using meteorology from the Princeton dataset.

varies to a smaller extent and therefore models aiming at attributing IAV may not assign fertiliser a high priority.

2. Materials and methods

The statistical models require several inputs to function: planting and harvest dates determine the growing season which is used to find the seasonal meteorology which is used as a predictor of yield. The growing season sometimes crosses the end of the calendar year, here all yields are taken as relating to the time of planting. The yield data used to train the models was derived from the UN FAO (FAOSTAT, 2014) and was gridded onto the 0.5° grid used by the meteorological data using the nearest neighbour method for any grid cells that cross country borders. The UN FAO data is generally country scale, however Brazil, China, the USA and some other large countries supplied sub-national data. The Ag-GRID GGCMI harmonisation project produced data for planting and harvest of major crops and the maize, rice and wheat results were used to define the seasons (Elliott et al., 2015).

Two meteorological variables were selected as inputs for the statistical models: total seasonal rainfall and mean seasonal temperature. These variables were calculated from two climate forcing datasets. One is the updated and extended Princeton University Hydroclimatology Group Bias Corrected 59-yr (1948–2006) Meteorological Forcing Dataset originally described in Sheffield et al. (2006) and updated in Sheffield et al. (2012) (hereafter Princeton dataset). The second is the WATCH-Forcing-Data-ERA-Interim dataset described in Weedon et al. (2014) (hereafter WFDEI dataset).

The fertiliser data is the new input used in this study as an additional predictor of yield. The annual mean fertiliser data in kg/ha/yr were extracted at country level from the Supplementary data Annex 2 of Lassaletta et al. (2014), this country level data was subsequently gridded onto the 0.5° grid used by the meteorological data using the same method as the FAO yields. The fertiliser is a nitrogenous fertiliser with no information for phosphorous or potassium. The sources of nitrogen in the fertiliser dataset are described in Figure 5(c) of Lassaletta et al. (2014) where it is shown that the relative fraction of synthetic fertilisers is increasing with respect to organic fertilisers.

2.1. Model description

The statistical models were built using the robust linear model tool in MATLAB, the robust linear models are less sensitive to outliers than least squares models and were utilised for that purpose (Holland and Welsch, 1977). The reduction in the impact of the outliers is done using a bisquare weighting which weights values depending on their proximity to the fitted line. In each grid cell, for each crop (maize, rice and wheat) a model was developed.

The input yields, meteorological data and fertiliser input have been detrended before use in the statistical models. The natural log of the yield data was taken before detrending, this allows the model to show relative differences instead of absolute ones. Two degree polynomial detrending was selected over linear detrending (Lobell et al., 2011; Shi et al., 2013). The purpose of the models is to predict yield variability, therefore the input data have been detrended to prevent the models ascribing changes in yield to long term trends. To predict trends in yields would require other predictors related to technical improvement such as pesticides, irrigation and trends in fertiliser application. The detrending will remove long term changes in yield, such as increases from changes in phenology from breeding, or the deployment of pesticides. Step changes will not be removed using the detrending and this is a known vulnerability of the type of model used.

The equation solved by each grid cell is shown in Eq. (1) and generates separate parameters for each crop. Where Y is the natural log of the yield, T is mean seasonal temperature, P is total seasonal precipitation, F is total fertiliser amount, i is the index for the grid cell and t is the index for the year. Each model is run on data from 1961–2009 (Princeton) and 1979–2009 (WFDEI). This model style has previous been used to investigate crop response to climate e.g. Estes et al. (2013), Hernandez-Barrera et al. (2016), Lobell and Burke (2010), Wang et al. (2016), Zhou and Wang (2015).

$$Y_{it} = a_i + b_i T_{it} + c_i P_{it} + d_i F_{it} \tag{1}$$

Download English Version:

https://daneshyari.com/en/article/5761177

Download Persian Version:

https://daneshyari.com/article/5761177

Daneshyari.com