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Modelling fertiliser significance in three major crops

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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.

Keywords: Fertiliser, Statistical modelling, Maize, Rice, Wheat

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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); 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 inter-annual variability (IAV) of yield is driven entirely by climate, here we investigate

24 to what extent the contribution of fertilizer use modulates climate driven yield
25 IAV (Shi et al., 2013). The different amount of fertiliser could partly explain
26 why two regions of the same climate, experience a difference in yield and yield
27 variability. The addition of fertiliser as an input into simple statistical models
28 may also explain more of the variability in current yields which is important if
29 statistical models are to be used for future projections.

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

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

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

49 **2. Materials and Methods**

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

62 Two meteorological variables were selected as inputs for the statistical mod-
63 els: total seasonal rainfall and mean seasonal temperature. These variables
64 were calculated from two climate forcing datasets. One is the the updated and
65 extended Princeton University Hydroclimatology Group Bias Corrected 59-yr
66 (1948-2006) Meteorological Forcing Dataset originally described in Sheffield et al.
67 (2006) and updated in Sheffield et al. (2012) (hereafter Princeton dataset). The
68 second is the WATCH-Forcing-Data-ERA-Interim dataset described in Weedon et al.

69 (2014) (hereafter WFDEI dataset).

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

79 *2.1. Model description*

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

86 The input yields, meteorological data and fertiliser input have been de-
87 trended before use in the statistical models. The natural log of the yield data
88 was taken before detrending, this allows the model to show relative differences
89 instead of absolute ones. Two degree polynomial detrending was selected over
90 linear detrending (Lobell et al., 2011; Shi et al., 2013). The purpose of the mod-
91 els 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 Equation 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 previously 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).

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

2.2. Model validation

In the cases of models which do not arrive at a solution after a set number of iterations were discarded. This is the case for much of Russia, Ukraine, Central Asia, Uruguay and Mauritania for all crops in addition to Angola for maize and wheat. This exclusion of models without a solution accounts for less than 10% of maize and rice results, however for wheat 16.9% of the grid cells are removed

113 in the Princeton dataset and 26.9% for WFDEI. The large number of wheat
114 models that cannot find a solution are in the former USSR.

115 As to only focus on regions where the models are significant, any model which
116 does not have a significance value $p < 0.05$ is rejected from further analysis.
117 The significance values of the climate and fertiliser and climate only models are
118 shown in Figure 1. In almost all cases for the Princeton dataset the significance
119 value of the model improves with the addition of the fertiliser component to the
120 model. The use of fertiliser as an input to the model improves the significance of
121 the results in several regions. The results for significance value for the WFDEI
122 dataset (Figure 2) show a similar improvement to the Princeton dataset.

123 To test for collinearity in the input variables the variance inflation factor
124 (VIF) was calculated for each variable used in each model. A VIF value of 5
125 showing collinear results and values above 10 being highly collinear (Kutner et al.,
126 2004). The maximum VIF for the input variables for each crop are shown in
127 the Figure 3. These results show some collinearity in the input data which is
128 expected as temperature and precipitation are dependent on each other in the
129 climate system. Neither the Princeton nor the WFDEI dataset are found to be
130 highly collinear.

131 The addition of variables to a statistical model also allows greater freedom
132 in the parameter space at the cost of a less informative fit. The Akaike informa-
133 tion criterion (AIC) measures the amount of information lost by a model, in a
134 comparison between models the model with the minimum AIC is considered su-
135 perior (Akaike, 1974). For models with a finite sample size the AIC is corrected

136 and the AICc is calculated, this is shown in Figure 4. For almost all results
137 there is a decrease in AICc, however for maize in Ecuador for the Princeton
138 dataset there is an increase in AICc. In the WFDEI dataset models there is an
139 increase in AICc for a small number of cells in the US corn belt.

140 The above results show that the data is not overly collinear which means it
141 is suitable for use in the linear models, that the addition of the fertiliser data
142 to the model reduces the amount of information lost by the models and that in
143 some regions that the models are statistically significant.

144 **3. Results**

145 The input data to the models has been shown to be suitable and not strongly
146 collinear, in addition the models with the fertiliser variable have been shown to
147 explore more of the variability within the sample data. Finally the models are
148 also required to be statistically significant to a value of $p < 0.05$. To show
149 the impact of adding fertiliser to the model, both climate only and climate and
150 fertiliser models were built and analysed, the differences between their results
151 are presented here. The root mean square error (RMSE) for the models shows
152 how close they are to replicating the observed data and the standard deviation
153 of the model outputs compared to the inputs shows the fraction of the variability
154 explained. The RMSE and SD results are shown in Figures 5 and 6. The RMSE
155 for the models containing the fertiliser term vary between 1000 and 1500 kg/ha.
156 The models with fertiliser are an improvement over models without the fertiliser
157 input. The RMSE is generally below 1200 kg/ha for high yield areas such as

Indian, South African and South American maize, Indian and South East Asian rice and Eastern European and Turkish wheat. The R^2 is also calculated for each model and the difference between the climate and fertiliser and the climate only models recorded. As is shown in Figures 5, 6 and 7 the fertiliser inclusive models better capture the variability in the agronomic system.

The RMSE, SD and R^2 results show improvements in several countries with the addition of fertiliser into the statistical models. The Princeton dataset based models for maize improve the RMSE, SD and R^2 for yields in India, Pakistan, several East African countries (notably Uganda, Mozambique and South Africa), along with Argentina and Paraguay. The WFDEI dataset results for maize show similar improvements in many of the same countries, however the Indian results are not as good and there are improvements in results for Zimbabwe.

When adding fertiliser to the Princeton dataset, for rice, the improvement is found across several highly productive nations including India, Myanmar and Indonesia. The notable exception of China in the Princeton results is repeated for the WFDEI results and many of the countries show the same result.

The wheat results, primarily the RMSE and SD, are significantly improved over much of Europe, (Poland, Czech Republic, Slovakia, Bulgaria, Turkey) and in addition the Egyptian Nile delta. The WFDEI results mirror those from the Princeton dataset however they show smaller improvements.

The standard deviation results in Figure 6 show that in countries which do not show an improvement when accounting for fertilisers in predictors in the RMSE, the models using fertiliser as a predictor do explain more of the vari-

181 ability of the yields, in particular the representation of Indian crops is improved.
182 The standard deviation results are supported by the changes in the R^2 value
183 (Figure 7) where the correlation between the model outputs and the yield values
184 increases with the use of both climate and fertiliser data.

185 The improvements in the yield simulations in for grid cells for each model
186 is shown in Tables 1 and 2. For the Princeton dataset the number of cells with
187 an improvement in RMSE overwhelms the number where there is a reduction in
188 quality. The extra yield explained by the models with fertiliser is close to 18%.
189 The WFDEI dataset results are stronger with improvements of yield forecast
190 by approximately 23%.

191 4. Discussion

192 The results herein show that the addition of fertiliser as an input into sim-
193 ple linear models improves the representation of crop yields recorded in a 49
194 year dataset (Princeton) or a 31 year dataset (WFDEI). Similar linear models
195 have been used in several previous studies at multiple scales (Estes et al., 2013;
196 Hernandez-Barrera et al., 2016; Lobell and Burke, 2010; Wang et al., 2016; Zhou and Wang,
197 2015). These results agree with previous studies and show that linear models
198 have skill in reproducing observed yields. In contrast with Wang et al. (2016)
199 this study finds that the inclusion of fertiliser in the linear models is significant
200 for rice in China.

201 As discussed in Lobell (2013) the quality of the linear model outputs are
202 highly dependent on the inputs, in this study the models are limited by the

effectively country level nature of the fertiliser and yield values and by the single planting and harvest date which was used for all years. This means the models do not account for early or late planting or harvest which could be a response to a change in the seasonal meteorology. The models in the study are based on seasonal totals and thus do not take into account the time period of events such as heavy rain or delayed monsoons. This is in contrast to process based models with a daily resolution that will respond to changes in meteorology. The removal of the reliance on seasonal totals allows sub-seasonal variability to have an impact and this is missed by the linear models.

The use of polynomial detrending of the input data removes gradual change in the input variables (Hernandez-Barrera et al., 2016; Shi et al., 2013). This removes changes in yield due to breeding and technology improvements, changes in environmental drivers (e.g. carbon dioxide and climate trends) including the use of fertilisers themselves. Because these different factors contributing long term changes are difficult to disentangle and may differ between crop type and region, detrending is justified in this study focused on explaining inter-annual yield variations. Yields may present abrupt changes that can reflect shocks or artefacts in the census data and these discontinuities are not removed by polynomial detrending. As climate data has been used, the outputs on smaller nations are less robust, aberrations or instabilities in the model may cause anomalous in individual grid cells. Repeated experiments or averaging over multiple grid cells ameliorates this particular problem.

The models used in this work are based on use of nitrogen fertiliser only.

226 Many modern fertilisers are complexes of several important nutrients including
227 potassium or phosphorus. The absence of specific analysis on potassium or
228 phosphorus fertiliser data may lead to ascribing an increase in yield to nitrogen
229 fertiliser instead of the other compounds. The use of a more details model, with
230 specific nutrient channels would remove this weakness.

231 The methods used to develop these models could be combined with forecasts
232 of both climate and fertilizer additions to provide near term forecasts on the
233 relative impacts of climate change or changes in fertiliser use. Simple linear
234 models have been shown to be not notably worse than process based models in
235 the short term(Lobell and Asseng, 2017). Longer term assessments on the how
236 fertiliser use will impact yields requires a process based model with a nitrogen
237 scheme.

238 **5. Conclusions**

239 The use of simple linear models to simulate yields of three major crops,
240 maize, rice and wheat is shown to be statistically significant for several regions.
241 The use of fertiliser input into the linear models in addition to temperature and
242 precipitation inputs improves the estimation of the yield variability. The models
243 are shown to be valid for two inputs sources of temperature and precipitation
244 data, WFDEI and Princeton. The improvements in the simulations of the yield
245 with the addition of fertiliser into simple linear models strongly supports the
246 development of detailed nitrogen schemes in more complex process based models
247 which are suited to longer term projections.

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Figure 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.

Figure 2: 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 WFDEI dataset.

Figure 3: Maximum variance inflation factor for climate and fertiliser input data for models for maize (top), rice (middle) and wheat (bottom) with Princeton data on the left and WFDEI on the right.

Figure 4: Difference in AICc between climate and fertiliser and climate only models for maize (top), rice (middle) and wheat (bottom) with Princeton data on the left and WFDEI on the right.

Figure 5: Difference in RMSE between climate and fertiliser and climate only models for maize (top), rice (middle) and wheat (bottom) with Princeton data on the left and WFDEI on the right.

Figure 6: Difference in standard deviation between climate and fertiliser and climate only models for maize (top), rice (middle) and wheat (bottom) with Princeton data on the left and WFDEI on the right.

Figure 7: Difference in R^2 between climate and fertiliser and climate only models for maize (top), rice (middle) and wheat (bottom) with Princeton data on the left and WFDEI on the right.

Table 1: Improvements in yield estimate for climate and fertiliser models when compared with climate only models for the Princeton dataset.

Crop	Maize	Rice	Wheat
Improved cells	9968	8451	4918
Average improvement (kg/ha)	435	695	47
Weakened cells	4	0	0
Average weakening (kg/ha)	19	0	0
Total change (kg/ha)	434	695	472
Fraction of yield	17.4%	17.3%	19.7%

Table 2: Improvements in yield estimate for climate and fertiliser models when compared with climate only models for the WFDEI dataset.

Crop	Maize	Rice	Wheat
Improved cells	5168	2939	3704
Average improvement (kg/ha)	592	775	558
Weakened cells	13	22	2
Average weakening (kg/ha)	182	137	396
Total change (kg/ha)	590	768	557
Fraction of yield	23.5%	22.8%	23.6%