Modelling fertiliser significance in three major crops

Ben Parkes[a], Benjamin Sultan[a], Philippe Ciais[b], Xuhui Wang[b,1]

[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*

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

---

Email address: `ben.parkes@locean-ipsl.upmc.fr` (Ben Parkes)

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 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 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 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 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 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).

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

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

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

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

The addition of variables to a statistical model also allows greater freedom in the parameter space at the cost of a less informative fit. The Akaike information criterion (AIC) measures the amount of information lost by a model, in a comparison between models the model with the minimum AIC is considered superior (Akaike, 1974). For models with a finite sample size the AIC is corrected and the AICc is calculated, this is shown in Figure 4. For almost all results there is a decrease in AICc, however for maize in Ecuador for the Princeton dataset there is an increase in AICc. In the WFDEI dataset models there is an increase in AICc for a small number of cells in the US corn belt.

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

3. Results

The input data to the models has been shown to be suitable and not strongly collinear, in addition the models with the fertiliser variable have been shown to explore more of the variability within the sample data. Finally the models are also required to be statistically significant to a value of $p < 0.05$. To show the impact of adding fertiliser to the model, both climate only and climate and fertiliser models were built and analysed, the differences between their results are presented here. The root mean square error (RMSE) for the models shows how close they are to replicating the observed data and the standard deviation of the model outputs compared to the inputs shows the fraction of the variability explained. The RMSE and SD results are shown in Figures 5 and 6. The RMSE for the models containing the fertiliser term vary between 1000 and 1500 kg/ha. The models with fertiliser are an improvement over models without the fertiliser 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 variability of the yields, in particular the representation of Indian crops is improved. The standard deviation results are supported by the changes in the R^2 value (Figure 7) where the correlation between the model outputs and the yield values increases with the use of both climate and fertiliser data.

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

4. Discussion

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

As discussed in Lobell (2013) the quality of the linear model outputs are 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.

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

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

5. Conclusions

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

Acknowledgements

The research leading to these results has received funding from the European Union Seventh Framework Programme FP7/2007-2013 under grant agreement n^{0}603864. The authors would like to thank Lindsey Lee and Stewart Jennings at the University of Leeds for several productive conversations about statistical model development.

References

Akaike, H., 1974. A new look at the statistical model identification. IEEE Transactions on Automatic Control 19, 716–723. doi:10.1109/TAC.1974.1100705.

Bondeau, A., Smith, P.C., Zaehle, S., Schaphoff, S., Lucht, W., Cramer, W., Gerten, D., Lotze-campen, H., Mller, C., Reichstein, M., Smith, B., 2007. Modelling the role of agriculture for the 20th century global terrestrial carbon balance. Global Change Biology 13, 679–706. doi:10.1111/j.1365-2486.2006.01305.x.

Boote, K.J., Jones, J.W., White, J.W., Asseng, S., Lizaso, J.I., 2013. Putting mechanisms into crop production models. Plant, Cell & Environment 36, 1658–1672. doi:10.1111/pce.12119.

Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., Zimmer, D., Sierra, J., Bertuzzi, P., Burger, P., Bussire, F., Cabidoche, Y., Cellier, P., Debaeke, P., Gaudillre, J., Hnault, C., Maraux, F., Seguin, B., Sinoquet, H., 2003. An overview of the crop model stics. European Journal of Agronomy

18, 309 – 332. doi:http://dx.doi.org/10.1016/S1161-0301(02)00110-7. modelling Cropping Systems: Science, Software and Applications.

Elliott, J., Müller, C., Deryng, D., Chryssanthacopoulos, J., Boote, K.J., Büchner, M., Foster, I., Glotter, M., Heinke, J., Iizumi, T., Izaurralde, R.C., Mueller, N.D., Ray, D.K., Rosenzweig, C., Ruane, A.C., Sheffield, J., 2015. The global gridded crop model intercomparison: data and modeling protocols for phase 1 (v1.0). Geoscientific Model Development 8, 261–277. doi:10.5194/gmd-8-261-2015.

Estes, L.D., Beukes, H., Bradley, B.A., Debats, S.R., Oppenheimer, M., Ruane, A.C., Schulze, R., Tadross, M., 2013. Projected climate impacts to south african maize and wheat production in 2055: a comparison of empirical and mechanistic modeling approaches. Global Change Biology 19, 3762–3774. doi:10.1111/gcb.12325.

FAOSTAT, 2014. Food and Agriculture Organization of the United Nations: FAOSTAT Database. Online resource (http://data.fao.org/database?entryId=262b79ca-279c-4517-93de-ee3b7c7cb553). Latest update: 07 Mar 2014.

Gornott, C., Wechsung, F., 2016. Statistical regression models for assessing climate impacts on crop yields: A validation study for winter wheat and silage maize in germany. Agricultural and Forest Meteorology 217, 89 – 100. doi:http://dx.doi.org/10.1016/j.agrformet.2015.10.005.

Hernandez-Barrera, S., Rodriguez-Puebla, C., Challinor, A.J., 2016. Effects of diurnal temperature range and drought on wheat yield in spain. Theoretical and Applied Climatology , 1–17doi:10.1007/s00704-016-1779-9.

Holland, P.W., Welsch, R.E., 1977. Robust regression using iteratively reweighted least-squares. Communications in Statistics - Theory and Methods 6, 813–827. doi:10.1080/03610927708827533.

Iglesias, A., Garrote, L., Quiroga, S., Moneo, M., 2012. A regional comparison of the effects of climate change on agricultural crops in europe. Climatic Change 112, 29–46. doi:10.1007/s10584-011-0338-8.

Keating, B., Carberry, P., Hammer, G., Probert, M., Robertson, M., Holzworth, D., Huth, N., Hargreaves, J., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J., Silburn, M., Wang, E., Brown, S., Bristow, K., Asseng, S., Chapman, S., McCown, R., Freebairn, D., Smith, C., 2003. An overview of apsim, a model designed for farming systems simulation. European Journal of Agronomy 18, 267 – 288. doi:http://dx.doi.org/10.1016/S1161-0301(02)00108-9. modelling Cropping Systems: Science, Software and Applications.

Kutner, M., Nachtsheim, C., Neter, J., 2004. Applied Linear Regression Models. McGraw-Hill Irwin.

Lassaletta, L., Billen, G., Grizzetti, B., Anglade, J., Garnier, J., 2014. 50 year trends in nitrogen use efficiency of world cropping systems: the relationship between yield and nitrogen input to cropland. Environmental Research Letters 9, 105011.

Lobell, D.B., 2013. Errors in climate datasets and their effects on statistical crop models. Agricultural and Forest Meteorology 170, 58 – 66. doi:http://dx.doi.org/10.1016/j.agrformet.2012.05.013. agricultural prediction using climate model ensembles.

Lobell, D.B., Asseng, S., 2017. Comparing estimates of climate change impacts from process-based and statistical crop models. Environmental Research Letters 12, 015001.

Lobell, D.B., Burke, M.B., 2010. On the use of statistical models to predict crop yield responses to climate change. Agricultural and Forest Meteorology 150, 1443 – 1452. doi:http://dx.doi.org/10.1016/j.agrformet.2010.07.008.

Lobell, D.B., Schlenker, W., Costa-Roberts, J., 2011. Climate trends and global crop production since 1980. Science 333, 616–620. doi:10.1126/science.1204531, arXiv:http://www.sciencemag.org/content/333/6042/616.full.pdf.

Martre, P., Wallach, D., Asseng, S., Ewert, F., Jones, J.W., Rtter, R.P., Boote, K.J., Ruane, A.C., Thorburn, P.J., Cammarano, D., Hatfield, J.L., Rosenzweig, C., Aggarwal, P.K., Angulo, C., Basso, B., Bertuzzi, P., Biernath, C., Brisson, N., Challinor, A.J., Doltra, J., Gayler, S., Goldberg, R., Grant, R.F., Heng, L., Hooker, J., Hunt, L.A., Ingwersen, J., Izaurralde, R.C., Kersebaum, K.C., Mller, C., Kumar, S.N., Nendel, C., O'leary, G., Olesen, J.E., Osborne, T.M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M.A., Shcherbak, I., Steduto, P., Stckle, C.O., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., White, J.W., Wolf, J., 2015. Multimodel ensembles of wheat growth: many models are better than one. Global Change Biology 21, 911–925. doi:10.1111/gcb.12768.

Mueller, N.D., Gerber, J.S., Johnston, M., Ray, D.K., Ramankutty, N., Foley, J.A., 2012. Closing yield gaps through nutrient and water management. Nature 490, 254–257.

Müller, C., Elliott, J., Chryssanthacopoulos, J., Arneth, A., Balkovic, J., Ciais, P., Deryng, D., Folberth, C., Glotter, M., Hoek, S., Iizumi, T., Izaurralde, R.C., Jones, C., Khabarov, N., Lawrence, P., Liu, W., Olin, S., Pugh, T.A.M., Ray, D.K., Reddy, A., Rosenzweig, C., Ruane, A.C., Sakurai, G., Schmid, E., Skalsky, R., Song, C.X., Wang, X., de Wit, A., Yang, H., 2017. Global gridded crop model evaluation: benchmarking, skills, deficiencies and implications. Geoscientific Model Development 10, 1403–1422. doi:10.5194/gmd-10-1403-2017.

Sheffield, J., Goteti, G., Wood, E.F., 2006. Development of a 50-year high-resolution global dataset of meteorological forcings for land surface modeling. J. Climate 19, 3088–3111. doi:10.1175/JCLI3790.1.

Sheffield, J., Wood, E.F., Roderick, M.L., 2012. Little change in global drought over the past 60 years. Nature 491, 435–438.

Shi, W., Tao, F., Zhang, Z., 2013. A review on statistical models for identifying climate contributions to crop yields. Journal of Geographical Sciences 23, 567–576. doi:10.1007/s11442-013-1029-3.

Wang, X., Peng, L., Zhang, X., Yin, G., Zhao, C., Piao, S., 2014. Divergence of climate impacts on maize yield in northeast china. Agriculture, Ecosystems & Environment 196, 51 – 58. doi:http://doi.org/10.1016/j.agee.2014.06.009.

Wang, Z., Ye, T., Wang, J., Cheng, Z., Shi, P., 2016. Contribution of climatic and technological factors to crop yield: empirical evidence from late paddy rice in hunan province, china. Stochastic Environmental Research and Risk Assessment 30, 2019–2030. doi:10.1007/s00477-016-1215-9.

Weedon, G.P., Balsamo, G., Bellouin, N., Gomes, S., Best, M.J., Viterbo, P., 2014. The wfdei meteorological forcing data set: Watch forcing data methodology applied to era-interim reanalysis data. Water Resources Research 50, 7505–7514. doi:10.1002/2014WR015638.

White, J.W., Hoogenboom, G., Kimball, B.A., Wall, G.W., 2011. Methodologies for simulating impacts of climate change on crop production. Field Crops Research 124, 357 – 368. doi:http://dx.doi.org/10.1016/j.fcr.2011.07.001.

Wu, X., Vuichard, N., Ciais, P., Viovy, N., de Noblet-Ducoudré, N., Wang, X., Magliulo, V., Wattenbach, M., Vitale, L., Di Tommasi, P., Moors, E.J., Jans, W., Elbers, J., Ceschia, E., Tallec, T., Bernhofer, C., Grünwald, T., Moureaux, C., Manise, T., Ligne, A., Cellier, P., Loubet, B., Larmanou, E., Ripoche, D., 2016. Orchidee-crop (v0), a new process-based agro-land surface model: model description and evaluation over europe. Geoscientific Model Development 9, 857–873. doi:10.5194/gmd-9-857-2016.

Zhou, M., Wang, H., 2015. Potential impact of future climate change on crop yield in northeastern china. Advances in Atmospheric Sciences 32, 889–897. doi:10.1007/s00376-014-4161-9.

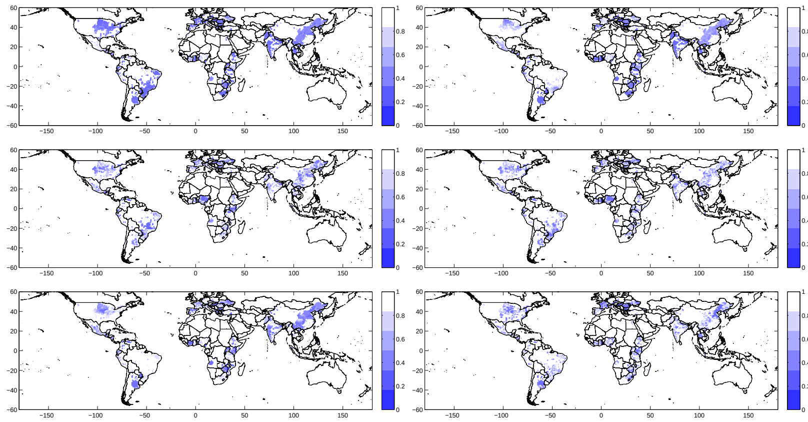

Figure 1: Significance values for models for climate only (left) and climate and fertiliser (right) for maize (top), rice (middle) and wheat (bottom) using meteorology from the Princeton dataset.

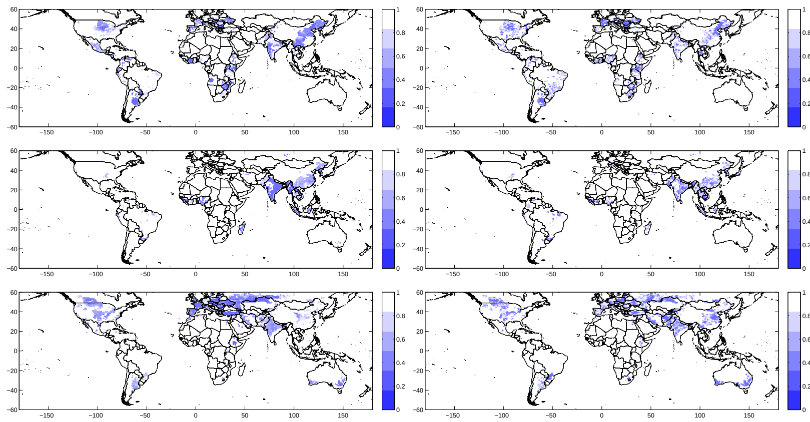

Figure 2: Significance values for models for climate only (left) and climate and fertiliser (right) for maize (top), rice (middle) and wheat (bottom) using meteorology from the WFDEI dataset.

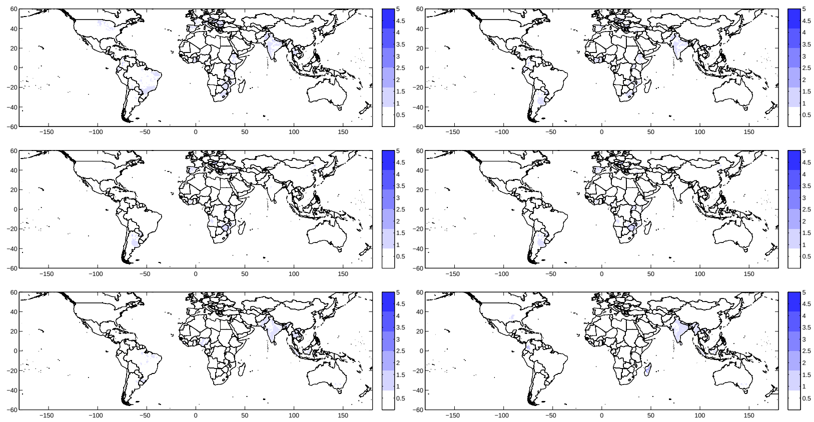

Figure 3: Maximum variance inflation factor for climate and fertiliser input data for models for maize (top), rice (middle) and wheat (bottom) with Princeton data on the left and WFDEI on the right.

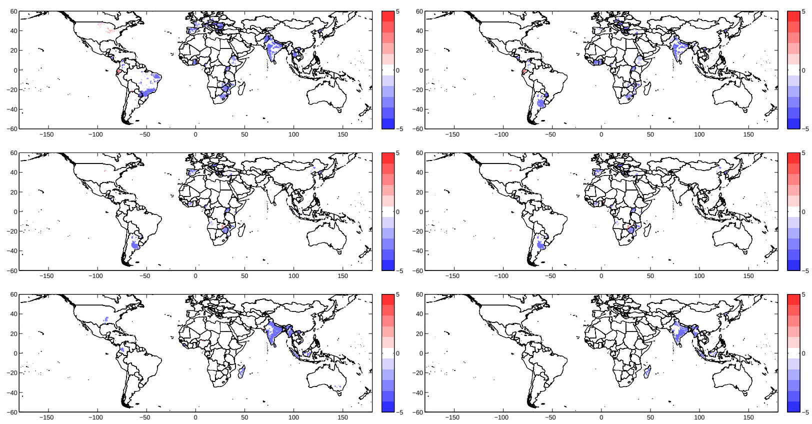

Figure 4: Difference in AICc between climate and fertiliser and climate only models for maize (top), rice (middle) and wheat (bottom) with Princeton data on the left and WFDEI on the right.

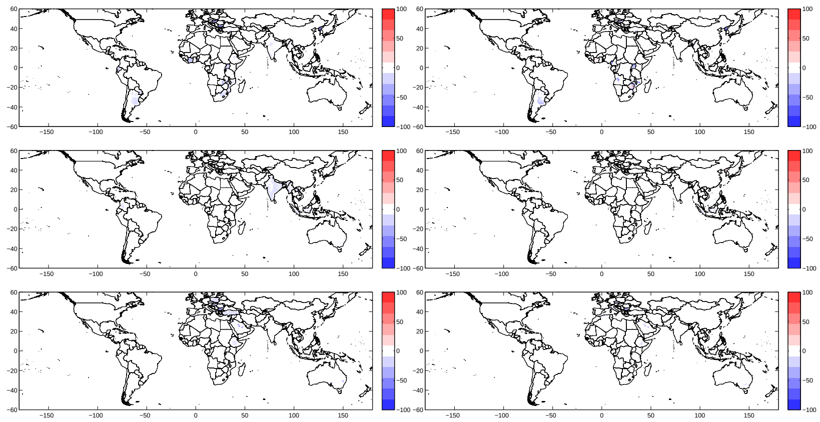

Figure 5: Difference in RMSE between climate and fertiliser and climate only models for maize (top), rice (middle) and wheat (bottom) with Princeton data on the left and WFDEI on the right.

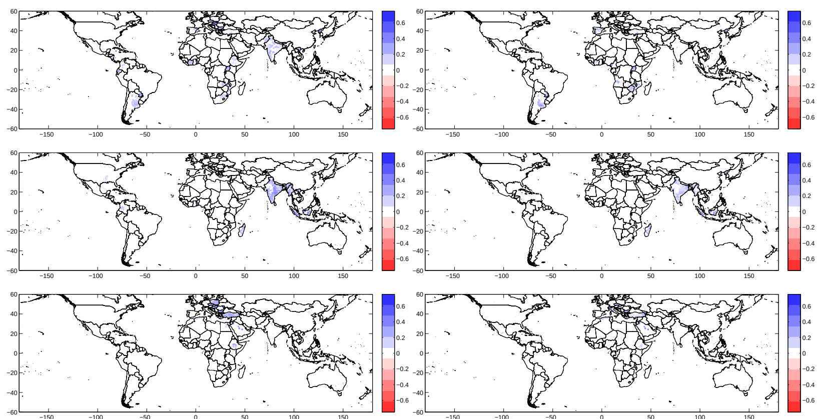

Figure 6: Difference in standard deviation between climate and fertiliser and climate only models for maize (top), rice (middle) and wheat (bottom) with Princeton data on the left and WFDEI on the right.

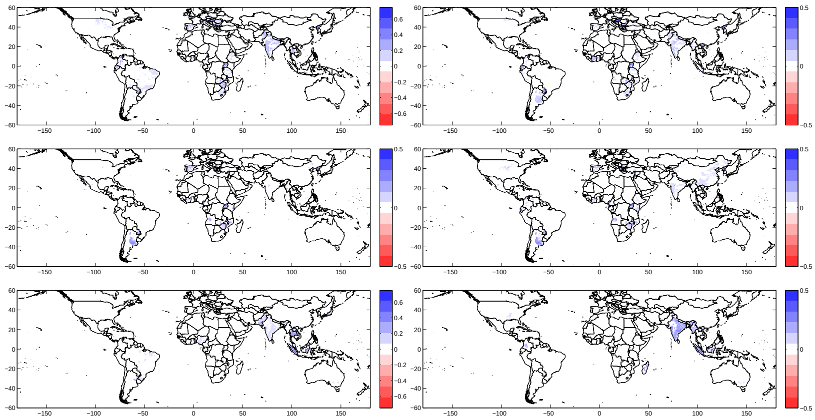

Figure 7: Difference in R^2 between climate and fertiliser and climate only models for maize (top), rice (middle) and wheat (bottom) with Princeton data on the left and WFDEI on the right.

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%