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Crop yield response to climate change varies with cropping intensity

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Running header: Cropping intensity, yield and climate change

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Abstract

Projections of the response of crop yield to climate change at different spatial scales are known to vary. However, understanding of the causes of systematic differences across scale is limited. Here, we hypothesise that heterogeneous cropping intensity is one source of scale dependency. Analysis of observed global data and regional crop modelling demonstrate that areas of high versus low cropping intensity can have systematically different yields, in both observations and simulations. Analysis of global crop data suggests that heterogeneity in cropping intensity is a likely source of scale dependency for a number of crops across the globe. Further crop modelling, and a meta-analysis of projected tropical maize yields, are used to assess the implications for climate change assessments. The results show that scale dependency is a potential source of systematic bias. We conclude that spatially comprehensive assessments of climate impacts based on yield alone, without accounting for cropping intensity, are prone to systematic overestimation of climate impacts. The findings therefore suggest a need for greater attention to crop suitability and land use change when assessing the impacts of climate change.

Introduction

Scale dependencies in biological and ecosystem function are a known phenomenon (e.g.Zhao & Liu, 2014). Relationships between species and environment vary according to the spatial scale of the analysis. One component of that difference arises from the intrinsic properties of the system, whilst a second contribution comes from choices made in the design of the study (Lechner et al., 2012). Important aspects of the study design include the spatial scale at which observations are available, and any choices regarding re-scaling of those observations prior to analysis. Observation and analysis at one or more spatial scales are used to make inferences regarding the intrinsic properties of a system, which may be expressed at a different spatial scale. The resulting potential for error in inference has led to ongoing refinement of methods (e.g.Hay et al., 2001).

Assessments of scale dependencies in agricultural systems have been used to address a range of questions. For example, remotely sensed data have been used to assess yield gaps across scales (e.g.Lobell, 2013); and gridded data has been used to understand the implications of scale dependencies for crop modelling (Folberth et al., 2012). Scale dependencies in climate change assessments have also been identified (e.g. Angulo et al., 2013, Hansen & Jones, 2000, Mearns et al., 2001). These studies have tended to treat scale dependencies as a source of model uncertainty by, for example, aggregating data prior to running a crop model (van Bussel et al., 2011a). The term 'aggregation error' is generally used to describe any crop model error resulting from the spatial averaging of either input data or crop model output.

Here, we hypothesise that heterogeneous cropping intensity is one source of scale dependency, so that choosing major growing regions for climate change impacts studies can produce different results to spatially comprehensive analyses. Major growing regions may have a tendency for higher yields, since crops tend to be grown where they are more productive. We refer to this tendency as the niche effect. Our metric for separating major from minor growing regions is cropping intensity – i.e. the fraction of land in a given region that is used to cultivate a given crop. Hence crop niches are those regions where, for a given crop, yields are higher where cultivation is intensely concentrated. This is in contrast to a crop where yields do not vary significantly with the area under cultivation. Our hypothesis can therefore be succinctly expressed as follows: for crops that exhibit a niche effect, heterogeneous cropping intensity causes scale dependency. We also hypothesise that, as has been observed in other studies, input weather aggregation error generates systematic differences in crop model results.

Materials and methods

We employ three sources of independent data for our analyses: observed yields and growing area data, regional crop modelling, and meta-analysis of crop modelling studies. The crop modelling focusses on West Africa, the meta-analysis on tropical maize growing regions, and observations range from within West Africa to global scale. Analyses of observed global data and regional crop modelling were used to assess whether or not areas of high versus low cropping intensity areas have systematically different yields. A subsequent crop modelling sensitivity analysis was used to test whether or not this effect has any implications for climate change studies.

Meta-analysis

The tropical maize data from an existing meta- analysis (Challinor et al., 2014b) were reanalysed to differentiate between yield projections on spatial scales above 3x3^{o} and those below 3x3^{o}. This threshold was chosen since it is typical of that of the climate models used in the studies in the meta-analysis. The data were categorised as being at scales either above or below 330x330km, corresponding approximately to 3 degree cells. Site-scale assessments were all categorised as less than 3 degrees. For subnational- and country-scale yield data, the area of the corresponding sub-national unit or country were compared directly to the area of a 330x330km square.

The procedure resulted in yield data, with associated local mean temperature change, from 223 maize simulations from 22 studies for range of maize-growing countries: Brazil, Burundi, Cameroon, Egypt, Ghana, India, Indonesia, Kenya, Mali, Mexico, Mozambique, Rwanda, South Africa, Tanzania and Uganda. Challinor et al. (2014b) contains detailed analysis of these data, including assessment of focal regions of the studies relative to the major cropping regions globally; and assessment of potential disproportionate contribution of a small number of global gridded studies to the total number of data points.

Crop modelling

A crop suitability model (Ramirez-Villegas et al., 2013) and a process-based crop growth and development model (Challinor et al., 2004) were used to assess the impact of aggregation and of cropping intensity. Yield and suitability simulations in regions of high cropped area are contrasted with analyses that include all grid cells. Simulations at two spatial scales were carried out using the same models, in order to assess the aggregation effect whilst excluding model structural differences as a possible cause of systematic differences in the results. To assess whether or not niche and aggregation effects would be likely to have an impact on climate change projections in the regions, a sensitivity analysis was conducted. Temperature and precipitation were varied systematically, using increments of 1K and 10%, respectively. Changes were applied to the whole domain. All percentage changes reported in the figures are with respect to the baseline of zero change in temperature or precipitation.

The General Large Area Model for annual crops (GLAM), which was used to simulate maize and groundnut yields, was designed to operate at regional scales and is therefore less complex in relation to field-scale models (Challinor et al., 2004). In GLAM, development is computed via a thermal time response function with three cardinal temperatures; biomass accumulation is calculated as the product of total crop transpiration and the transpiration efficiency; and yield is calculated using the total biomass and a time-integrated rate of change in the harvest index. Transpiration is in GLAM limited by soil structure, plant structure, available energy and water. Leaf area is parameterised using a potential rate of growth that is reduced by water stress and the yield gap parameter (C_{YG}). Required inputs to GLAM are soil hydrological parameters (permanent wilting point, field capacity and saturation point), daily values of maximum and minimum temperature, downwards shortwave solar radiation, and precipitation.

For maize, all GLAM parameters except thermal time requirements were derived from Bergamaschi et al. (2007), Greatrex (2012) and Osborne et al. (2013). Thermal time coefficients were derived following Challinor et al. (2004), by calibrating to a mean duration based on cultivar parameterisations in another crop model, in this case CERES-maize. Cultivars with a range of thermal requirements were simulated with CERES-maize. The cultivar whose duration was closest to 120 days was then used to calculate the thermal durations required for GLAM. We chose 120 days as a typical duration of a cropping season in West Africa (Hartkamp et al., 2000, Sacks et al., 2010). For groundnut, parameter values were obtained from Vermeulen et al. (2013) . An intelligent sowing window was used, whereby planting occurs on the first day on which the soil is sufficiently moist. The sowing window began with the first day of the weather input data (see below). For both maize and groundnut, two values of the yield gap parameter (C_{YG}) were used, in order to reduce the dependency on a single calibration (see Appendix S1).

Crop suitability was modelled using EcoCrop, which is a relatively simple suitability-based model. It has been previously used to understand the geography of crop suitability and its responses to climate change for various crops, including banana (Ramirez et al., 2011, Van den Bergh et al., 2012), cassava (Ceballos et al., 2011, Jarvis et al., 2012), sorghum (Ramirez-Villegas et al., 2013) and groundnut (Vermeulen et al., 2013) . EcoCrop has also been used to project future shifts in suitable areas for key staple foods across the globe (Lane & Jarvis, 2007). Previous studies have reported that EcoCrop results are consistent with other approaches (Ramirez-Villegas et al., 2013, Vermeulen et al., 2013).

EcoCrop uses fixed environmental ranges as inputs to produce a suitability index. Suitability is calculated separately for temperature and precipitation for a prescribed growing season using a set of four thresholds for each variable. Optimal conditions occur when a site is between the minimum and maximum optimum for both variables. Unsuitable conditions occur when a site is either above or below the absolute (or marginal) thresholds for either temperature or precipitation. Between optimum and absolute thresholds suitability is calculated using a linear regression with the optimal value assigned to 100% and the marginal one assigned to 0% suitability.

In this study, EcoCrop parameter sets for simulating maize and groundnut were used to analyse the impacts of scale for climate change impacts projections. Parameters for maize were derived from Jarvis et al. (2012) and Cairns et al. (2013), further adjusted using literature review. In particular, a number of studies (Jones et al., 1986, Kim et al., 2007, Lobell et al., 2011, Sánchez et al., 2014, Schlenker & Lobell, 2010) were used to identify optimum and marginal temperatures for the crop. For precipitation, the CIMMYT mega-environments dataset were used to identify the relevant thresholds (Bellon et al., 2005, Hodson et al., 2002). For groundnut, parameter values were obtained from (Vermeulen et al., 2013) and (Ramirez-Villegas, 2014) and further compared with those used in the GLAM (Challinor et al., 2004) and CROPGRO-PNUT (Boote et al., 1998, Dugan, 2004) models.

<u>Study region and model input data</u>

We focus on West Africa mainly due to its large spatial variation in precipitation and temperature (Baron et al., 2005, Berg et al., 2010), but also partly due to the availability of high-resolution convection-resolving regional climate simulations. Along the chosen portion of West Africa (Figure S1), total precipitation varies between 300 and 3,500 mm per year, with most precipitation occurring between June and October, during the monsoon. Mean June-October temperatures across the region also vary substantially, with the lowest temperatures (around 10 ºC) occurring in the Cameroonian Highlands and the highest temperatures (around 30-35 ºC) occurring across the Sahelian countries (Burkina Faso, Senegal, Niger and Mali). As a consequence of this spatial variation and heterogeneity in crop management, crop yields are highly variable, and substantial yield gaps have been reported (Licker et al., 2010, Monfreda et al., 2008).

The two crop models were driven with 12km x 12km weather simulations with explicit parameterisation of convection, taken from the CASCADE (Cloud System Resolving Modeling of the Tropical Atmosphere) project (Birch et al., 2014) . A total of 144 calendar days, between 1st June 2006 through 22nd October 2006, were available. Simulated precipitation, maximum temperature, minimum temperature and downwards shortwave radiative flux were used as input to the crop models. Mean temperature was calculated as the average between maximum and minimum temperatures. Simulated daily data were aggregated to monthly values for use with EcoCrop. The mean 144-day temperature and precipitation for the region are shown in Figure S1.

Aggregation error was assessed by first aggregating the 12-km CASCADE data to a 3x3 degree grid using bilinear interpolation. The coarser-scale simulations will have less intense events and more drizzle than the 12km simulations. Thus storms active on the 12km grid will contribute to light rainfall across the whole 3 degree domain, as happens in coarse-grid climate simulations. This method avoids dependency of results on choice of climate model (see e.g.Angulo et al., 2013). Soils inputs for the crop yield model were regridded from the FAO digital soil map of the world using the same methodology employed in Vermeulen et al. (2013) .

In addition to the CASCADE data, high-resolution climatological data from WorldClim (Hijmans et al., 2005) were used to drive the crop suitability model. WorldClim is a high-resolution (30 arc-sec) global database of climatological means of monthly precipitation, mean, minimum and maximum temperatures. WorldClim is currently the most used climate database for niche modelling and has been tested for robustness in Africa (Ramirez-Villegas

& Challinor, 2012) and the globe (Hijmans et al., 2005). For West Africa, previous studies have reported low uncertainty associated with the interpolations in WorldClim. We aggregated the 30 arc-sec data to a resolution of 5 arc-min in order to reduce computational needs. We used WorldClim to drive the EcoCrop model and then assess its output against observational data.

We used both planting and harvesting data (Sacks et al., 2010) to constrain the growing period in the crop suitability model. This dataset comprises the largest up to date database of crop planting and harvesting dates. The maize dataset consists of 192 observations that cover ca. 88 % of the maize harvested areas worldwide. The groundnut dataset consists of 40 observations that comprise ca. 57 % of global harvested areas.

Results

Meta-analysis

Fig. 1 shows the meta-analysis of Challinor et al. (2014b) , reanalysed to differentiate between yield projections on spatial scales above 3x3^o and those below 3x3^o. The figure contains 223 simulations of tropical maize under climate change in a range of locations, conducted with a range of crop and climate models. All yield projections are with respect to a baseline simulation with no climate change. Ranges of crop yield at any given temperature could be due to differences in the model used and in the model inputs, notably precipitation. The observed systematic difference between the two spatial scales of analysis could be due to a combination of factors: model structural differences, the locations chosen, and the spatial scale of the analysis. However, systematic differences are unlikely to be caused by random differences between studies. Hence, given the large range of models and locations used in the meta-analysis, the spatial scale of the analysis is likely to be a causal factor in explaining the systematic differences in Fig. 1. These scale differences may arise because of the spatial scale of the model simulations and/or the methods used to aggregate modelled yields (van Bussel et al., 2011a, van Bussel et al., 2011b). There is also, potentially, a systematic relationship between the spatial scale of the simulations and whether or not they focus on a region of high intensity cropping: sites chosen for detailed crop modelling analyses are likely to be in regions that are important for that particular crop.

Distinguishing crop niches using data and models

Evaluation of the results from both models (Appendix S1) indicated that the output could reliably be used to investigate the niche effect. Observed data on yield and area harvested for maize (Monfreda et al., 2008) were analysed together with model results to assess our hypotheses.

Observed yield and cropping area data indicate the existence of crop niching. Both maize and groundnut show a relatively small number of grid cells with high cropping intensity. Just 2.52% of maize grid cells, and 1.31% of groundnut grid cells, have a fractional growing area greater than 0.1. 5.32% of groundnut grid cells have a fractional growing area greater than 0.05. Fig. 2 shows the observed niche effect for both maize and groundnut. It was constructed by analysing yield data first across all grid cells, and second across grid cells with high growing area. The mean yields are similar in both sets of data for groundnut, but not for maize. Hence we can identify, for West Africa, that maize is a "niched" crop; whilst for groundnut the niche signal is less clear.

Crop yield simulations also indicate the existence of maize crop niching. For two different values of C_{YG}, GLAM represents well the difference between the maize simulations grouped i. across all regions and ii. in niche regions alone (Figure S2). In agreement with data (Fig. 2), for groundnut a smaller distinction is seen. Thus, GLAM adequately represents the distinction (maize) or lack of distinction (groundnut) between niche and non-niche environments that is seen in Fig. 2. The mean yields are similar in both sets of data for groundnut, but not for maize. Note, however, that even for groundnut the two distributions still show a bias towards higher yields when only high-cultivation cells are analysed.

The EcoCrop results (Appendix S1) show that the areas in which groundnut and maize are grown are areas where the model simulates high suitability. In addition, for maize, mean suitability is higher when the analysis is restricted to the high-cultivation cells; whilst for groundnut the two means are the same. This result is consistent with Fig. 2. Maize has a large number of grid cells in which suitability is high. Groundnut, in contrast, is grown over a greater range of suitability environments than maize, including more marginal environments. Thus the crop suitability simulations also indicate the existence of crop niching for maize.

Sensitivity analysis

The sensitivity analysis was conducted to assess whether or not the niche effect would likely result in systematically different responses to climate change across regions of high versus low cropping intensity. It was also used to test aggregation error. First, temperature alone was varied. For maize (Fig. 3), a niche effect (difference between the squares and crosses) is seen in mean yields, but no aggregation effect (circles vs. crosses). This effect becomes more pronounced as temperature increases. Figure S3 shows the full range of values from the temperature sensitivity analysis. Whilst the niche effect as evident in mean yields is relatively weak compared to the full range, the signal is seen in GLAM in the mean, minimum, maximum, upper quartile and lower quartile; i.e. it is systematic.

For groundnut, no aggregation effect is seen, and any niche effect is marginal (Figure S4). Whilst the aggregation effect is insignificant at the domain-wide level for both crops, it can be significant in particular regions. Grid cells G and M (see Fig. 2) contain respectively dry and wet environments (Figure S1), and grid cell G manifests aggregation error, whilst cell M does not (Appendix S2).

One key difference between Figs. 3 and 1 is that Fig. 1 includes changes in precipitation, whilst Fig. 3 does not. The results of the full maize sensitivity analysis, where both temperature and precipitation were varied, are presented in Fig. 4. For both yield and suitability, the niche effect is more pronounced at lower precipitation than at higher precipitation. Whilst the reductions in crop suitability are relatively small, analysis of absolute values of suitability shows that the number of grid cells suitable for cultivation decreases by up to 30 percent (Appendix S3).

Ongoing increases in the spatial resolution of climate models mean that 3 degrees is no longer a common resolution for impacts modelling. a reproduction of Fig. 3b based on 1x1 degree weather data and corresponding crop yield simulations showed results that are consistent to those at 3 degrees (Figure S5).

Discussion

Implications for crop productivity assessments

There are a number of implications of niche and aggregation error for both individual modelling studies and for the synthesising of information about climate change impacts.

Whilst aggregation error was not evident at the domain-wide level in this study, evidence here and elsewhere (Baron et al., 2005, Mearns et al., 2001) suggests that coarse-scale simulations in a range of environments are often affected. Aggregation error has also been detected through variation in phenology resulting from aggregation of sowing dates and temperature (van Bussel et al., 2011a, van Bussel et al., 2011b). It is also evident in the optimisation procedure: calibrated crop model parameters can vary significantly with the size of the grid used (Iizumi et al., 2014). Aggregation error is difficult to predict, not least because climate model simulations at different spatial scales will produce different errors in aggregated precipitation, and because downscaling and bias-correction of crop model inputs also introduce errors. High resolution simulations can reduce aggregation error. However, if regional-scale yields are the quantity of interest then aggregation will still be needed at the model output stage, a process that can itself result in significant error (Angulo et al., 2013).

For niched crops – that is, crops where regions of high growing area coincide with regions of higher yield – the choice of study location can have a clear and systematic impact on projected yield changes. This issue is not confined to West Africa. Fig. 5 presents a simple country-scale analysis of niching for maize, confirming that maize is a niched crop in West Africa. The figure also highlights other crops and countries where the same behaviour is seen, e.g. rice in a number of countries, and soybean in North and South America. This observed niche effect, whilst varying in form across crops and regions (Figure S6), is of clear significance for understanding climate change impacts.

One reason for the niche effect is that the baseline yields are higher in niche regions, in both observations (Fig. 2) and in the model simulations (Figure S2). Similar absolute changes in yield, in response to climate change, therefore produce smaller percentage changes in niche regions. Under the majority of the temperature and precipitation changes tested in our sensitivity analysis, the mean of yields in niche regions decreases by more, in absolute terms, than that of all cultivated regions taken together (Figure S7). Direct comparison of percentage changes in yield across environments with different cropping intensities can therefore be misleading. In particular, analysis of yield changes across all regions, assessed together and treating percentages changes as directly comparable, can result in a systematic overestimation of the impacts of climate change.

Measuring changes in production, as well as or instead of crop yield (Deryng et al., 2014), by definition corrects for heterogeneity in cropping intensity. However, future growing area is unknown. The projected emergence of novel climates (Burke et al., 2009) suggests that a focus on current major growing areas, without testing for potential changes, may lead to errors. At decadal timescales, land use change is therefore an important part of crop productivity assessments. It acts as a driver of changes in production (Schroter et al., 2005) and both a response to (Olesen & Bindi, 2002), and cause of (Feddema et al., 2005), climate change. This suggests a need for studies that combine suitability models, and/or Agro-climatic indices (Trnka et al., 2011), with crop growth and development models and high quality data (Avellan et al., 2012). The fact that the skill of models can also be higher where cropping intensity is greater (Folberth et al., 2012) is promising in this context.

<u>Synthesising knowledge on climate impacts</u>

How should the response of yield to temperature in Fig 1 be interpreted in the light of the above analyses? Niche and/or aggregation error may contribute to systematic differences in yield projections. If smaller-scale yield projections are chosen such that they focus on regions of greater importance for maize production, then a niche effect may be present. In this event, the results from the smaller-scale crop models will be more representative of the expected changes in food production. The corresponding projected percentage reductions in food production, as a function of temperature and across large regions, will then be smaller than the reductions in yield. This effect is observed in the maize simulations presented here (Table 1).

The differences between yield and production changes presented in Table 1 are relatively small compared to the spread of yield values in Fig. 1. This is not surprising given that for both yield and production at any given temperature, there will be a range of different locations, precipitation, subseasonal temperatures, solar radiation, soils, and crop models. Each set of simulations will most likely have different model skill and different values of baseline yields.

As more studies are added to meta-analyses, the range of yields increases, which may be interpreted as an increase in uncertainty (Rotter, 2014) . However, uncertainty in the central tendencies, which measure the aggregate response of crops to local temperature increase, does not increase as data are added (Challinor et al., 2014b) . Clearly it is important to separate explained from unexplained variation in model results (Lehmann & Rillig, 2014) . Future work might draw on progress made in the broader area of cross-scale analysis in ecology (Lechner et al., 2012). Communicating the underlying issues surrounding uncertainty is also critical. Different interpretations of uncertainty ranges cause different conclusions to be reached, even amongst experts within a given field (Wesselink et al., 2014).

Model structural differences are another component of the spread in Fig. 1. Differences between models can be greater than differences introduced by aggregation of input weather data (Angulo et al., 2013). Consistent with what was found here, Rosenzweig et al. (2014) found that the inclusion of ecosystem-based models increased the ranges of simulated yields, compared to assessments with site-based models alone. Assessing consilience in processes, rather than in numerical model output, can reduce uncertainty (Challinor et al., 2013, Challinor & Wheeler, 2008). Key processes such as response to temperature (Koehler et al., 2013) and CO2 (Tausz et al., 2013) can vary significantly between different crop varieties and different crop models. Constantly challenging models with data, and recognising the different strengths and weaknesses of different modelling approaches, can also reduce uncertainty (Challinor et al., 2014a).

As the number of studies and methods used for climate impacts continues to grow, meta-analyses will include an increasing array of models and underlying assumptions. Differences in results from these methods are important and useful, since understanding and decomposing yield ranges can reduce uncertainty and aid understanding. Coordinated international programmes are instrumental in facilitating the intercomparisons needed for this work (Asseng et al., 2013, Rosenzweig et al., 2014).

Conclusions

Three independent lines of evidence point to the existence of a niche effect in maize in West Africa, and global data suggest that this effect is widespread in other crops and regions. The increasing array of climate impacts models should be used in a way that is cognisant of scale differences. Further, assessments of climate impacts based on yield alone, without accounting for cropping intensity, are prone to systematic overestimation of climate impacts. These findings therefore suggest a need for greater attention to crop suitability and land use change when assessing the impacts of climate change. In particular, future studies might combine suitability models, and/or Agro-climatic indices, with crop growth and development models and high quality data.

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Supporting Information legends

Appendix S1. Crop model evaluation

Appendix S2. Analysis of aggregation error

Appendix S3. Presence-absence analysis

Tables

Temp. change	1°C	2 °C	3 °C	4 °C	5 °C
Yield	14.7	27.8	39.6	50.7	61.2
Production	13.4	25.1	35.9	46.1	56.6

Table 1. Mean percentage reduction in crop yield and production as a function of temperature for the full set of 12km simulations. Yield values are the same as those shown in Fig. 3

Figure legends

Figure 1. The effect of spatial scale on projected yield change under local warming. Data taken from the tropical maize panel of Fig. 1 of (Challinor et al., 2014b), and re-analysed according to the spatial scale of the projected yield (see Methods).

Figure 2. Observed yield histograms and maps of fraction area harvested for maize (a,c), and groundnut (b,d), constructed using data from the M3-crops dataset (Monfreda et al., 2008). Blue lines in (a) and (b) are for all grid cells where the crop is grown. Red lines restrict the analysis to the highest intensity of cropped areas (the choice of 10% and 5% thresholds is explained in the Supplementary text). Blue squares in (c) and (d) correspond to the 3x3 degrees grid cells used for testing for aggregation error. Grid cells G and M are used in the main text to illustrate aggregation. Cell G has high groundnut cultivation, whilst cell M is a region of high maize cultivation.

Figure 3. Temperature sensitivity analysis for maize yield with two different values of the calibration parameter (C_{YG}=1 in panel (a), C_{YG}=0.5 in panel (b), and for maize suitability (c).

y-axis shows percentage change in crop yield or suitability, averaged across the grid cells indicated.

Figure 4. Simulated GLAM maize yield and EcoCrop suitability changes (percent) in response to temperature and precipitation perturbations. Average yield change across all 12km grid cells from all GLAM simulations with two different values of CYG (a,c) contrast with results from the high cropping intensity areas only (b,d). Corresponding EcoCrop suitability changes are also shown (e,f).

Figure 5. Difference in yields between areas of high maize cultivation intensity (top 10 % of area harvested within the country) and areas of low maize cultivation intensity (bottom 10 % of area harvested within the country). White areas are countries where the crop is not grown. Red colour scale indicates where high cropping intensity is coincident with higher yields, on a country scale. Grey areas indicate where the converse is true. Data taken from Monfreda et al. (2008).