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Spatial variation of crop yield response to climate change in East Africa

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ABSTRACT

There is general consensus that the impacts of climate change on agriculture will add significantly to the development challenges of ensuring food security and reducing poverty, particularly in Africa. While these changes will influence agriculture at a broad scale, regional or country-level assessments can miss critical detail. We use high-resolution methods to generate characteristic daily weather data for a combination of different future emission scenarios and climate models to drive detailed simulation models of the maize and bean crops. For the East African region, there is considerable spatial and temporal variation in this crop response. We evaluate the response of maize and beans to a changing climate, as a prelude to detailed targeting of options that can help smallholder households adapt. The results argue strongly against the idea of large, spatially contiguous development domains for identifying and implementing adaptation options, particularly in regions with large variations in topography and current average temperatures. Rather, they underline the importance of localised, community-based efforts to increase local adaptive capacity, take advantage of changes that may lead to increased crop and livestock productivity where this is possible, and to buffer the situations where increased stresses are likely.

1. Introduction

Climate change poses a serious and continuing threat to development. Scholes and Biggs (2004), referring to Sub-Saharan Africa as the food crisis epicentre of the world, conclude that projected climate change during the first half of the twenty-first century will make this situation worse. Climate change will add burdens to those who are already poor and vulnerable (IPCC, 2007). At the same time, agriculture in Sub-Saharan Africa will continue to play a crucial role through its direct and indirect impacts on poverty, as well as in providing an indispensable platform for wider economic growth that reduces poverty far beyond the rural and agricultural sectors (DFID, 2005).

Overall, crop yields in Africa may fall by 10–20% to 2050 because of warming and drying, but there are places where yield losses may be much more severe, as well as areas where crop yields may increase (Jones and Thornton, 2003). Many developing countries in Africa are seen as being highly vulnerable to climate variability and change (Slingo et al., 2005), in part because they have only a limited capacity to adapt to changing circumstances (Thomas and Twyman, 2005). A high reliance on natural resources, limited ability to adapt financially and institutionally, low per capita Gross Domestic Product (GDP) and high poverty, and a lack of safety nets mean that the challenges for development are considerable (Thomas and Twyman, 2005).

Despite this, there is considerable and increasing activity on the part of development agencies and governments to come to grips with these challenges, including the development of appropriate adaptation strategies. Given the scale of the problems involved, development agencies could greatly benefit from information that quantifies the impacts that may arise, so that development assistance can be targeted in appropriate places, depending on the development objectives that are being pursued. There are, however, considerable knowledge gaps concerning the interacting and multiple stresses on the vulnerability of the poor in Africa. There is a critical need to undertake analytical assessments of vulnerability to increased climatic variability and climate change, to better understand the implications for poverty reduction as well as to be able to assess adaptation initiatives (Huq and Reid, 2005; Nyong, 2005).

Some vulnerability mapping has been carried out for the continent, including a preliminary attempt to help locate critical research activities and identify areas that may be severely affected by climate change and where agricultural populations are already

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vulnerable, environmentally and socially (Thornton et al., 2006). These "hotspots" include the mixed arid–semiarid systems in the Sahel, arid–semiarid rangeland systems in parts of eastern Africa, the coastal regions of eastern Africa, and many of the drier zones of southern Africa, for example. However, there is a need for better and multi-level vulnerability analyses to help target adaptation work, because there is considerable spatial heterogeneity of not only the impacts of climate change but also households' access to resources, poverty levels, and ability to cope. There is also a critical need for better understanding of the information needs of decision-makers concerning climate change and variability, and tools need to be designed and implemented that can help meet these needs. While coping with climate change and variability is not a new challenge for African farmers, existing coping mechanisms may not be up to the challenges posed by the changes projected. The situation is made more complex by the fact that while we know something about the changes possible in climate in future years, we know much less about likely changes in climate variability and the probabilities of extreme events. Particularly for vulnerable people who are highly dependent on natural resources for their livelihoods, the impacts of extreme events, particularly the lower tails of probability distributions, may have a social and economic importance that far outweighs their apparent probability of occurrence. Increases in mean precipitation are likely to be associated with increases in variability (IPCC, 2007). In several regions, including parts of Africa, inter-annual climatic variability is strongly related to El Niño-Southern Oscillation (ENSO) events, and thus will be affected by changes in ENSO behaviour (Conway et al., 2007). More work is needed on the issue of changing weather variability in the future and what its impacts may be.

Even without considering changes in weather variability as a result of climate change, the patterns of crop yield impacts may be highly heterogeneous. Much of the agricultural impacts work to date has been carried out at relatively low spatial resolution, often at the scale of the globe, region, or country (for example, Parry et al., 2004; Cline, 2007; Lobell et al., 2008). Particularly for organizations that work with a "pro-poor" mandate in developing countries, in addition to the relatively broad-brush information that such studies provide, there is a need for more detailed information on the impacts of climate change on agricultural systems, so that effective adaptation options can be appropriately targeted. In this paper, we build on previous work (Jones and Thornton, 2003) that identified possible country-level changes in maize production to the middle of this century. Here we investigate in more detail the different types of crop response to climate change as represented by a combination of two climate models and two contrasting greenhouse-gas emission scenarios. For the East Africa region, we analyse the spatial differences in simulated main-season maize and secondary-season *Phaseolus* bean yields to 2050, and attempt some simple characterisation of crop response. The object of doing this is to assess the possibility of using such information for preliminary targeting of adaptation options at relatively high resolution. The next section of the paper outlines the methods used. Section 3 presents some simulation results, and the discussion in Section 4 sets out what we see as the major implications of the results for climate change impact assessment and adaptation targeting work in an African context.

2. Methods

A block diagram of the methods used is shown in Fig. 1, made up of strands dealing with climate and weather data, soils data, crop and crop management data, and the crop models used. These elements are described below.

2.1. Scenarios of future climate

For looking at different scenarios of climate change to 2050, the dataset TYN SC 2.0 was used (Mitchell et al., 2004). The variables used from this dataset were the diurnal temperature range, precipitation and average daily temperature on a monthly basis. The data cover the global land surface at a resolution of 0.5° latitude and longitude, and cover the period 2001–2100. There are 20 climate change scenarios in the complete dataset. The climate change scenarios are made up of all permutations of five Atmosphere-Ocean General Circulation Models (AOGCMs) and four emission scenarios, A1FI, A2, B1, B2 (SRES, Special Report on Emissions Scenarios, IPCC, 2000). The month-to-month and year-to-year variations are superimposed on top of the averaged climate changes taken from the models; these are taken from the gridded observations in a companion dataset, CRU TS 2.0 (New et al., 2002). The two datasets together thus provide complete time-series for the period 1901–2100.

Instead of the dataset of New et al. (2002), we used the 1-km interpolated climate grid for the globe named WorldCLIM (Hijmans et al., 2005), which we took to be representative of current climatic conditions (most of the data cover the period 1960–1990). This uses data from a number of databases, including the climate database at the International Centre for Tropical Agriculture. WorldCLIM uses thin plate smoothing with a fixed lapse rate employing the program ANUSPLIN. The algorithm is described in Hutchinson (1989). To save computing time, we reassembled the climate grid to a resolution of 10 arc-min to make the analysis programmes run faster. This grid file of climate normals we took to be representative of current conditions for the region. Each pixel in the file has latitude, longitude, elevation, and monthly values for average daily temperature (°C), average daily diurnal temperature variation (°C), and average monthly rainfall (mm).

We then prepared similar climate grid files for several combinations of the five GCMs and four SRES scenarios, for the years 2015, 2030, 2045 and 2060. To do this, quadratic regressions were fitted to every pixel at the resolution of the TYN SC 2.0 dataset ($0.5 \times 0.5°$ latitude and longitude) for the period 1985–2060 at 15-year intervals (i.e., six points). The regression fit was excellent in all areas apart from some polar regions, and the root mean square error (RMSE) was negligible. To generalize the process, we formed files of the three regression coefficients and the RMSE associated with each pixel (these are difference data associated with a particular combination of GCM and SRES scenario).

To interpolate back to the 10-min grids, the differences between the monthly rainfalls, temperatures and diurnal temperature ranges were calculated from the regression equations for each pixel in the coarse GCM grid. For each pixel in the 10-min grid, the interpolated value was obtained by inverse square distance weighting; details of the algorithm can be found in Jones and Gladkov (2001) and Jones and Thornton (2000).

There are considerable differences between SRES scenario and between the different GCMs, in terms of projected changes in temperatures, rainfall and length of growing periods in regions of Africa. The simulation of crop growth and development for the region of East Africa at a resolution of about 18 km (10 min of arc) takes many hours of computing time, and so we decided to concentrate on a subset of the GCMs and emission scenarios. In terms of selecting among the five GCMs, an analysis by McHugh (2005) on multi-model trends in rainfall for East Africa suggests that certain GCMs are better able to simulate observed rainfall patterns in this region than others. Two of these are included in the TYN SC 2.0 dataset, the Hadley Centre Coupled Model version 3, HadCM3 (Mitchell et al., 1998), and the European Centre Hamburg

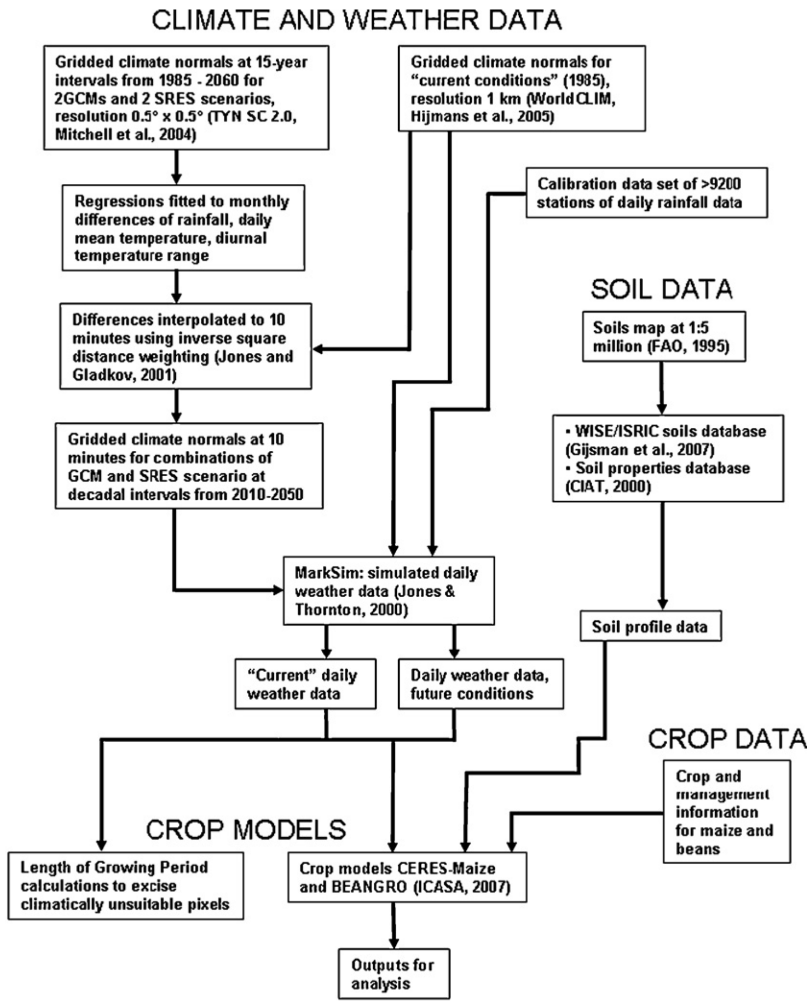

Fig. 1. Block diagram of the methods used in relation to climate and weather data, soils data, crop and crop management data, and the crop models.

GCM version 4 of the Max Planck Institute for Meteorology, ECHam4 (Roeckner et al., 1996). ECHam4 is a "wet" model—the rainfall differences projected under the four SRES scenarios from 2000 to 2050 are the largest of all the five GCMs in the TYN SC 2.0 dataset. On the other hand, the HadCM3 is a "drier" model; rainfall differences for the four scenarios between 2000 and 2050 are the lowest or among the lowest for all the GCMs in the dataset. We used these two GCMs for the analyses presented below. For emission scenarios, we chose a low-emission scenario (B1) and a high-emission scenario (A1F1), which span the range of best estimates of temperature change to 2090–2099 relative to 1980–1999 (IPCC, 2007). The full range of variation in the original TYN SC 2.0 dataset (minus the ECHam4 model runs, which were added to a subsequent version of the dataset) in terms of annual global-mean temperature anomalies relative to 1961–1990 between GCMs and scenarios is shown in Mitchell et al. (2004, p. 14). While the differences between the SRES scenarios become much more marked by 2100 and beyond, in terms of impacts on temperature, even by 2050 there are substantial differences between the A1FI and B1 scenarios. The changes in annual global-mean temperature (relative to 1961–1990) range from about 1.0 to 1.8 °C for the B1 scenario and from 1.6 to 2.8 °C for the A1FI scenario, depending on the GCM used. Our choices of combination of GCM and emission scenario from this dataset thus span a wide range of projected temperature and rainfall changes.

To generate daily data characteristic of whichever climate normals were being used, we used the weather generator MarkSim (Jones and Thornton, 2000). MarkSim simulates the variance of monthly and annual rainfall for sites in the tropics and subtropics by carrying out annual random resampling of certain of the model's own parameters. Patterns can be discerned in the parameter values that are typical for certain types of climate (Jones and Thornton, 1997). Because of this, MarkSim can be used to interpolate daily rainfall data for places where data do not exist. Regression models were developed that predict the Markov model parameters within certain restricted climate sets (Jones and Thornton, 1999). MarkSim then identifies the climate set relevant to any required point on the globe using interpolated climate surfaces and evaluates the model parameters for that point (Jones and Thornton, 2000). These surfaces are based on historical data from stations with more than 12 years of record over the period 1920–1990. MarkSim estimates daily maximum and minimum air temperatures and daily solar radiation values from monthly means using the methods originating with Richardson (1981). Monthly solar radiation is estimated from temperatures, longitude and latitude using the model of Donatelli and Campbell (1997).

2.2. Simulating cropping in the study region

For the work reported here, the study area is East Africa. This is part of a broader project designed to address questions of how land-use change affects climate, and how climate change affects land use, by looking at societal and environmental systems across space at multiple scales, from the global climate to regional vegetative dynamics to local decision-making by farmers and herders (Olson et al., 2008). The study region is the area between longitude 28°E to 42°E and latitude 12°S to 6°N. It covers all of Kenya, Uganda, Tanzania, Rwanda and Burundi, and parts of Ethiopia, Congo, Malawi and Mozambique. As in a previous study of cropping impacts (Jones and Thornton, 2003), we used maize as a test crop, because of its prevalence in the study region. To identify the likely (current and possibly future) maize-growing areas in the region, we carried out a triage of the climate pixels. We eliminated those pixels with growing seasons shorter than 40 days. To calculate length of growing period, we proceeded as follows. For each 10-min pixel in the study region, the climate normals data were read from the appropriate gridded file and interpolated to daily data using the method of Jones (1987). Potential evapotranspiration was calculated by the method of Linacre (1977). The water balance was calculated using WATBAL (see Jones, 1987, for the source). This uses the method of Keig and McAlpine (1974). It calculates the available soil water, runoff, water deficiency and the actual to potential evapotranspiration ratio (Ea/Et). The source code is a simplified version of Reddy (1979). The ratio Ea/Et is calculated from a square root function that fits the three points supplied by Reddy depending on soil water holding capacity. A moderate soil water holding capacity of 100 mm was assumed for all soils. On running the water balance simulation, the number of days with Ea/Et greater than 0.5 were counted as potential growing days from day-of-year 1 to day-of-year 365. A further restriction was placed to eliminate cold highland areas. Days with average temperature less than 9 °C were not counted as growing days even if water was not limiting. We converted the Food and Agriculture Organization soils map of the world coverage at a scale of 1:5 million (FAO, 1995) to a 10-min grid and identified all soils with agricultural potential in each climate pixel. This resulted in 6074 pixels in the region, with an average of 4.0 different soil types per pixel.

To simulate the growth, development and yield of the maize crop in these pixels, we used the model CERES-Maize (Ritchie et al., 1998), as currently implemented in version 4 of the Decision Support System for Agrotechnology Transfer (ICASA, 2007). CERES-Maize uses a daily time step, and calculates crop phasic and morphological development using temperature, day length and genetic characteristics. Development and growth processes are influenced by water and nitrogen balance submodels (Ritchie et al., 1998).

In terms of crop management, we ran simulations using a relatively short-season Kenyan variety as a proxy for a well-adapted generic maize variety. We assumed current smallholder cultural practices: planting was assumed to occur automatically, once the soil profile had received a thorough wetting at the start of the primary rains, and the crop was planted at a typical density of 3.7 plants/m^2. For all simulations, a nominal amount (5 kg/ha) of inorganic N was applied to the crop at planting. The model was reinitialised at the start of each season's run to make the simulations independent.

Bimodal rainfall patterns are common in the study region, and there are quite large areas where two growing seasons occur per year. For these areas, we simulated bean production also. To do this, beans were planted automatically after the maize crop had been harvested, again five consecutive days of a full soil profile being the signal to plant. If there was no secondary season, then beans were not planted, or if there was a secondary season but it was very short, then the beans would fail anyway. Strictly, the secondary crop here relates to a growing season that is not necessarily a separate, secondary season, but also is one long (or long enough) season to allow both maize and beans to be grown. To simulate the bean crop, we used the version of BEANGRO (Hoogenboom et al., 1994) as currently implemented in the DSSAT version 4. As for maize, simulated cultural practices reflect regional management. We grew one variety throughout the region (Diacol Calima, JW White, personal communication), and it was planted at a typically low 8 plants/m^2.

For all agriculturally suitable soil types in the study region, defined on the basis of the soil unit ratings in FAO (1978), we used representative profiles from the International Soils Reference and Information Centre's World Inventory of Soil Emission Potentials (WISE) database (Batjes and Bridges, 1994), as modified and reformatted by Gijsman et al. (2007).

The DSSAT crop models have been extensively tested in many parts of the world. Jones et al. (2003) refer to 15 studies in Africa that involved detailed crop model calibration and validation, several of which involved the testing of CERES-Maize in the study region (see, for example, Muchena and Iglesias, 1995; Thornton et al., 1995; Wafula, 1995; Schulze, 2000). While there are various sources of uncertainty in crop model simulations, careful calibration and validation can commonly result in simulated yields being within 10% of observed yields, and sometimes much closer agreement is possible (Jones et al., 2003). In this study we carried out no detailed testing of the models, but the simulated yields obtained are certainly characteristic of the levels of yield currently obtained by smallholders growing maize and beans in low-input, rain-fed conditions in much of the region.

We carried out 30 replicates (different weather years) for the following scenarios: the baseline, using current climate normals; and five time slices (2010, 2020, 2030, 2040, and 2050) for each of the four combinations of two GCMs (HadCM3 and ECHam4) and two SRES scenarios (A1F1 and B1). For all simulations, carbon dioxide concentrations were held constant at 330 ppm. Each simulation run for both maize and bean crops for the study region took about 24 h of computing time, and all runs were completed on two computers over a 30-day period.

3. Results

Fig. 2A shows average simulated maize yields when grown in the primary season under current climatic conditions, together with the coefficient of variation of this simulated yield (30 replicates). Similarly, Fig. 2B shows the average simulated bean yields in the secondary season where this is feasible and their coefficient of variation. As noted above, these maps do not show where maize and beans are currently grown; they merely show simulated yields in areas where they could be grown.

3.1. Aggregate production impacts

The results of simulations for the four scenario combinations are summarised in Table 1, in terms of the percentage change in "regional production" that is projected under each combination to 2050, assuming that all pixels are cropped as shown in Fig. 2 and that this cropping pattern does not change in the meantime. As expected, regional production changes differ depending on SRES scenario, but there are also some differences between GCM used. For the study region, the impacts of the ECHam4 model are projected to be more severe than those projected with the HadCM3 model, although the 11–15% production loss is still very much in line with earlier figures for all of Sub-Saharan Africa obtained using similar methods by Jones and Thornton (2003). At this aggregate level, both maize and beans appear to be similarly affected, as the percentage contribution of each crop to the total production figure

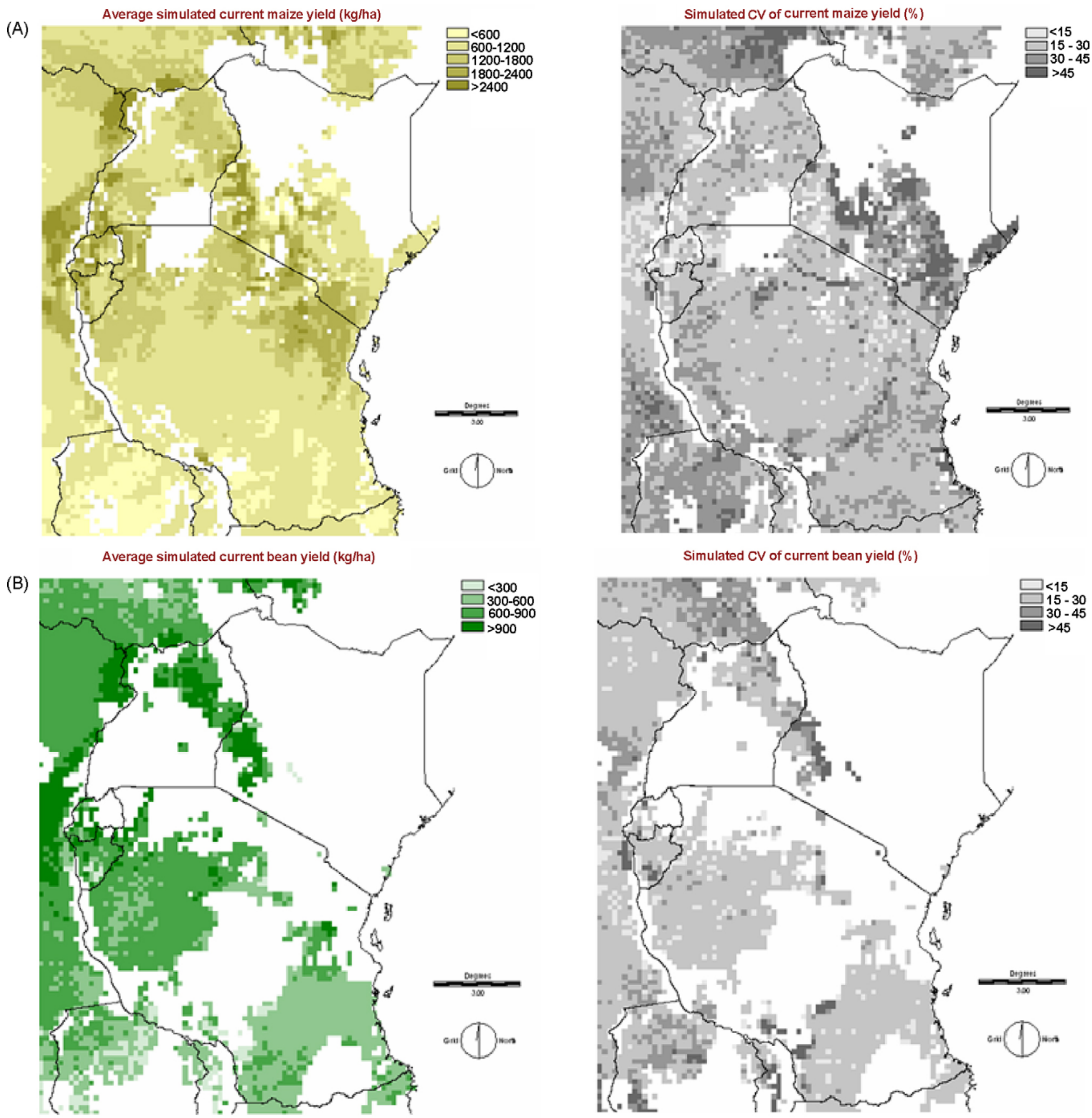

Fig. 2. (A) Simulated primary-season maize yields under current climatic conditions, mean of 30 replicates (kg/ha, left-hand panel), and the associated coefficient of variation of maize yields (%, right-hand panel). (B) Simulated secondary-season bean yields under current climatic conditions, mean of 30 replicates (kg/ha, left-hand panel), and the associated coefficient of variation of bean yields (%, right-hand panel).

Table 1
Simulated production differences in the study region to 2050, for two GCMs (HadCM3 and ECHam4) and two scenarios (A1FI and B1).

	Production change compared with baseline	Contribution of primary-season maize (%)	Contribution of secondary-season beans (%)
Baseline (1990–2000)		75	25
HadCM3 A1FI	−11%	77	23
HadCM3 B1	−1%	75	25
ECHam4 A1FI	−15%	77	23
ECHam4 B1	−3%	75	25

Production calculated as mean crop yield (kg/ha) multiplied by the land area in the pixel that is agriculturally suitable (ha) summed over all cropped pixels (primary-season maize plus secondary-season bean production, if any).

does not vary much across either SRES scenario or GCM projection. As in the Jones and Thornton (2003) study, we are assuming the continued use of current varieties and cultural practices. Plant breeding and agronomic research will not stand still, of course, and will more than make up such projected aggregate production losses. When the results are looked at in more detail, however, there are greater production changes (gains as well as losses) to be addressed.

3.2. Spatial heterogeneity of production impacts

Table 2 summarises yield changes for both beans and maize in terms of the percentages of the areas cropped that undergo a

Table 2
Percentages of cropped pixels exhibiting yield differences from the baseline to 2030 and 2050. Results are shown for four combinations of GCM, HadCM3 (HD) and ECHam4 (EC) and two SRES scenarios, A1FI and B1.

	Bean					Maize				
	−High	−Mod	No change	+Mod	+High	−High	−Mod	No change	+Mod	+High
HD A1FI										
2030	9	24	27	20	20	5	30	34	23	7
2050	49	16	8	8	18	14	30	28	20	8
HD B1										
2030	5	20	31	24	19	3	27	39	25	5
2050	14	26	22	17	21	9	30	30	23	8
EC A1FI										
2030	13	28	23	18	18	10	34	31	18	6
2050	56	14	7	7	16	33	32	16	12	7
EC B1										
2030	6	24	29	22	17	6	33	36	20	5
2050	20	28	19	14	18	14	35	27	17	6
Col 1	2	3	4	5	6	7	8	9	10	11

−High: >20% loss. −Mod: 5–20% loss. No change: ±5%. +Mod: 5–20% gain. +High: >20% gain.

severe yield loss (>20%, "−High"), a moderate yield loss (5–20%, "−Mod"), no yield change (±5%, "no change"), a moderate yield increase (5–20%, "+Mod"), and a substantial yield increase (>20%, "+High"), between the baseline year and the time slices shown (2030 and 2050). These pixel percentages are shown for the four combinations of GCM and scenario. Thus for the HadCM3 GCM and A1FI scenario combination ("HDA1" in Table 2), for example, the percentage of pixels that showed "no change" in bean yields decreased from 27% in 2030 to only 8% by 2050. For maize, the percentage of "no change" pixels decreased from 34% in 2030 to 21% in 2050 (values in each line across columns 2–6 (bean) sum to 100%, as do columns 7–11 for maize).

Several points may be made about the results in Table 2. First, there are differences between the two SRES scenarios used. As noted above in Section 2.1, this is to be expected, given that even by 2050 there are substantial differences in global temperature anomalies (compared with the period 1961–1990) for the GCMs used. Yield changes under the low emissions scenario, B1, are similar in direction to those under A1FI, but are generally more muted. For example, 22% of bean pixels are classified as "no change" to 2050 for the B1 scenario using the Hadley CM3 model, compared with only 8% for the A1FI scenario (column 4 in Table 2). Even for the B1 scenario, however, by 2050 moderate to severe percentage yield losses are projected to occur for both beans and maize in about 40% of pixels.

Second, there are some differences between the yield losses projected using the two GCMs. For the study region, pixel counts for percentage yield losses tend to be higher for the ECHam4 model

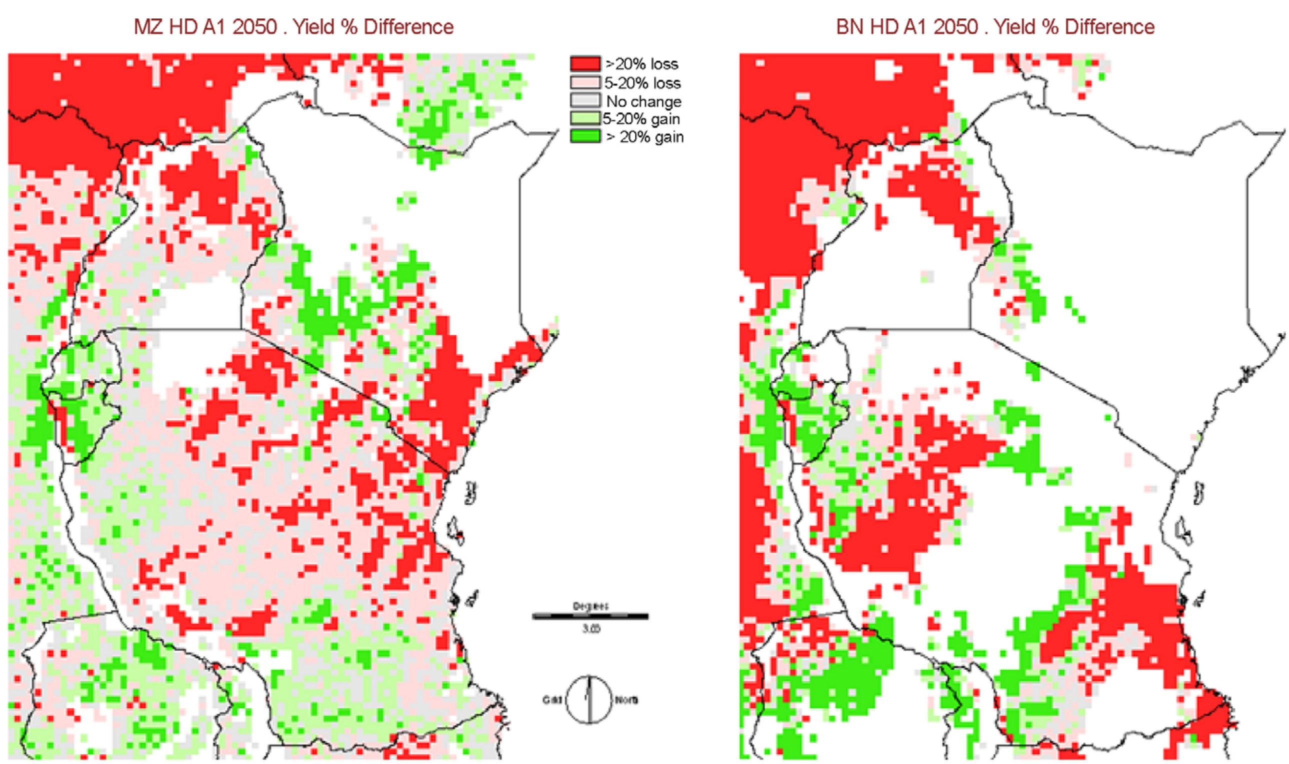

Fig. 3. Simulated maize (left-hand panel) and secondary-season bean (right-hand panel) percentage yield differences to 2050 compared with current conditions, for the HadCM3 and A1FI scenario combination, mapped in areas of statistically significant yield differences ($p \leq 0.05$).

than for the HadCM3 model for the same time slice. This is also shown by the aggregate production change shown in Table 1 for these two GCMs. For example, for the A1FI scenario, severe and moderate percentage yield losses in maize occur in 44% of pixels for the HadCM3 model versus 65% of pixels for the ECHam4 model (columns 7 and 8 in Table 2).

Third, there are considerable differences between the two crops, primary-season maize and secondary-season beans. While noting that percentage changes are reported only for those pixels that are cropped (the proportion of maize pixels being considerably larger than that for secondary-season beans), bean yields in general are more sensitive to projected climate changes than maize yields. This is to be expected, given that maize is a C_4 crop and will be more tolerant of higher temperatures than a C_3 crop such as beans (Jones and Thornton, 2003). For all four GCM–scenario combinations, a larger percentage of bean pixels than maize pixels suffer severe yield reductions to 2050 (columns 2 and 7 in Table 2).

Fourth, while there are negative impacts on bean and maize yields in many pixels, there are also positive impacts on yields in some pixels for both crops, regardless of scenario and GCM. There are positive impacts in a larger proportion of bean pixels for all scenarios–GCM combinations than for maize pixels (compare bean totals in columns 5 and 6 with maize totals in columns 10 and 11, Table 2).

Simulated yield differences are mapped in Fig. 3, in terms of the percentage change in the mean yield compared with the baseline yield for primary-season maize and secondary-season beans to 2050 using the HadCM3 model projections and the SRES A1FI scenario. These percentage changes are mapped only in those areas where there is a statistically significant difference in mean yield

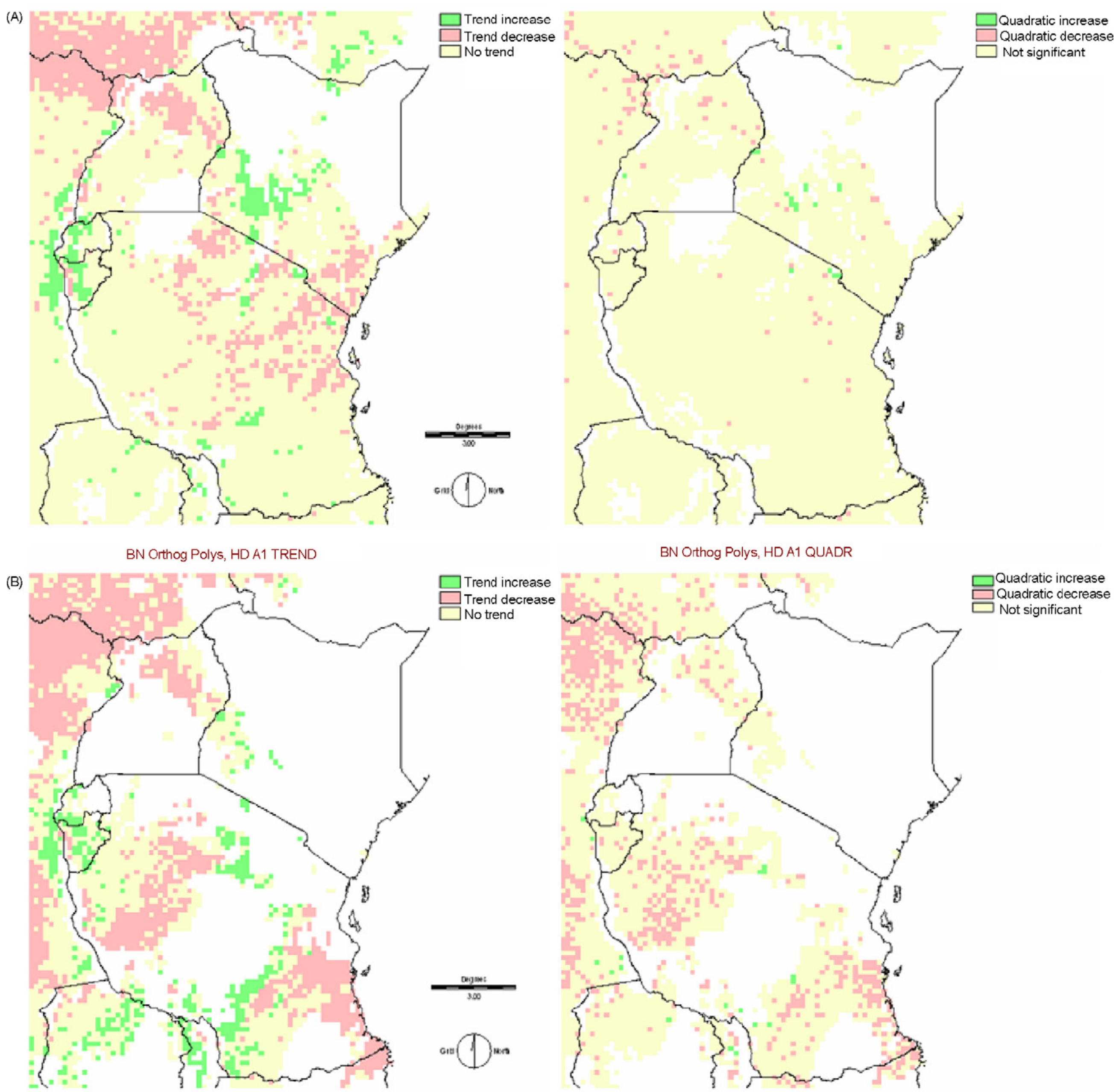

Fig. 4. (A) Results of orthogonal polynomial regressions of maize yields, 2000–2050, HadCM3 and A1FI. Significant ($p \leq 0.05$) yield trend (left-hand panel). Significant ($p \leq 0.05$) quadratic term (right-hand panel). (B) Results of orthogonal polynomial regressions on secondary-season bean yields, 2000–2050, HadCM3 and A1FI. Significant ($p \leq 0.05$) yield trend (left-hand panel). Significant ($p \leq 0.05$) quadratic term (right-hand panel).

from 2000 to 2050 (t-test, $n = 30$ replicates, $p = 0.05$). Fig. 3 underlines the considerable spatial heterogeneity in simulated yield changes to 2050. Maize yields to 2050 are reduced by 20% or more for large areas in the north-west of the study region (northern Uganda, southern Sudan) and for the more semiarid areas of Kenya and Tanzania where maize cropping is possible. Most of these losses are in the range 200–700 kg/ha, although in some pixels, they are larger than this. By contrast, maize yields are projected to increase in some of the highland areas of the region: in the southern Ethiopian highlands, the central and western highlands of Kenya, and the Great Lakes Region, mostly by between 200 and 700 kg/ha. Projected yield losses in secondary-season beans are rather more widespread, with many parts experiencing yield losses of up to 350 kg/ha and more. Other areas, such as the western highlands of Kenya, the Great Lakes Region, and northern Mozambique, are projected to see substantial increases in bean yields.

3.3. Temporal heterogeneity of production impacts

To analyse the temporal trends in mean yields for maize and beans from the baseline year to 2050, we fitted orthogonal polynomial regressions using the methods given in Fisher and Yates (1967). This allowed us to calculate orthogonal trend coefficients and quadratic terms for the yields in each pixel simulated at the six time slices to 2050, for a given GCM–scenario combination. We calculated F statistics on the significance of the trend and quadratic terms. We added in the variance of the baseline yields to the regression sums of squares, to estimate the correct residual variance for the regression terms. We then classified each pixel in terms of whether the trend was significantly positive (an overall yield increase from 2000 to 2050), significantly negative (a yield decrease to 2050), or statistically not significant. We then did another classification in terms of whether the quadratic term was significantly positive (a decrease in yield from 2000 followed by an increase in yield to 2050), significantly negative (an increase in yield from 2000 followed by a decrease to 2050), or statistically not significant (all F tests at $p = 0.05$). Results are mapped for the HadCM3-A1FI combination for maize yields (Fig. 4A) and secondary-season bean yields (Fig. 4B).

For maize, there are clear decreasing yield trends in the upper north-west of the region (northern Uganda, southern Sudan) and in lowland areas of Kenya and Tanzania. Increasing maize yields are found in the highland areas of central Kenya and the Great Lakes Region (Fig. 4A left). There are relatively few pixels where the quadratic term is significant (i.e., where a turning point exists). There are a few areas in the north-western parts of the study region, where weather patterns in the years subsequent to 2000 bring about some increase in maize yields, only for these increases then to be wiped out in subsequent years and yields to decrease. There are a few areas in central Kenya and in the region of Kilimanjaro where yields are stable or decrease initially, only to increase in subsequent decades. The situation for beans (Fig. 4B) is more dynamic. Yield trends in some of the highland areas are positive, and negative in other places, particularly the coastal areas. In many of the latter areas (Fig. 4B right), there are initial increases in bean yields (these are quite widespread), followed by decreases in later decades.

3.4. Characterising production impacts

The results reported above can be largely explained in relation to changes in temperature. The explanatory power of average temperature as a predictor of future (simulated) yield changes for

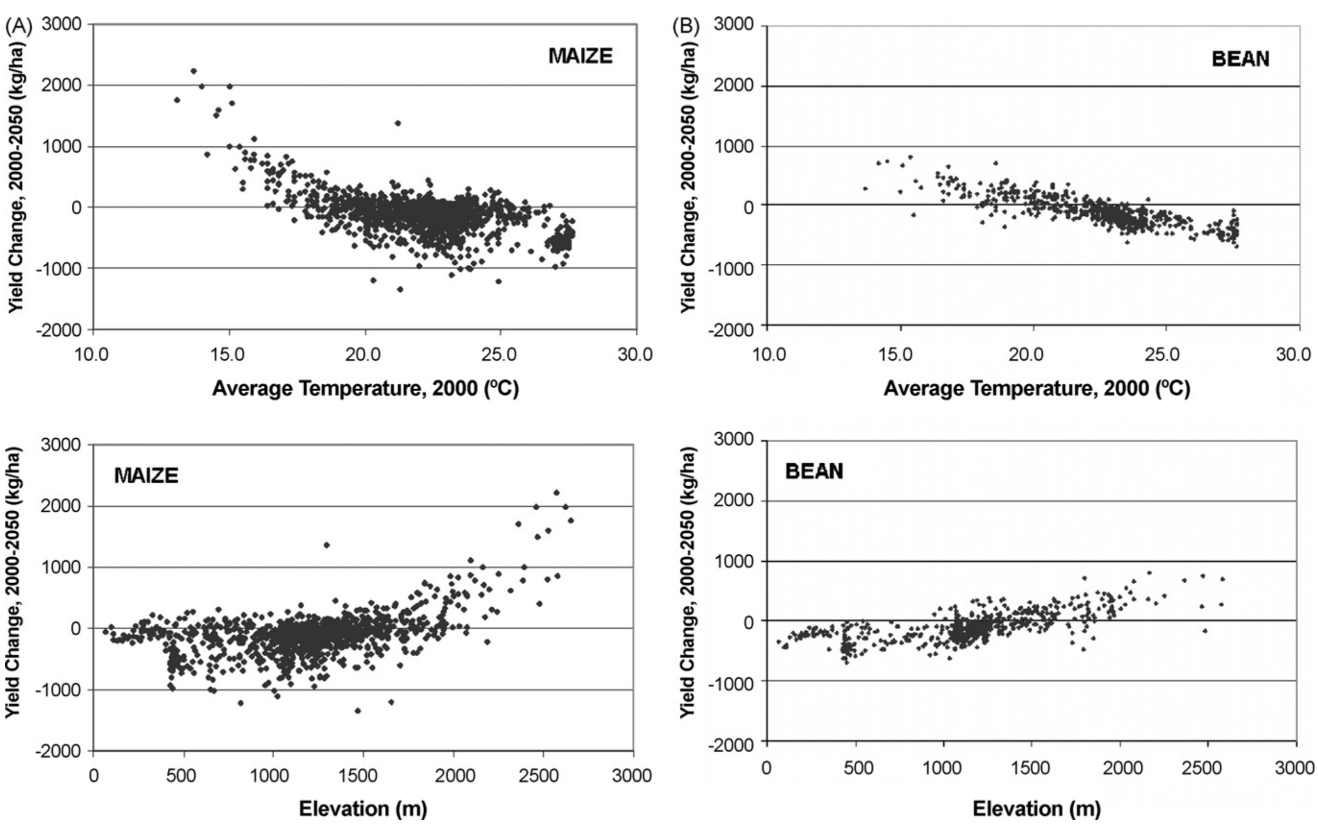

Fig. 5. (A) The relationship between yield changes from 2000 to 2050 for "cropped and simulated" maize pixels and average daily temperature for current conditions (top) and elevation (bottom), HadCM3 and A1FI. (B) The relationship between yield changes from 2000 to 2050 for "cropped and simulated" secondary-season bean pixels and average daily temperature for current conditions (top) and elevation (bottom), HadCM3 and A1FI.

Table 3
Role of simulated water stress in maize yield differences in selected pixels in Kenya over the period 2000–2050, for the HadCM3 GCM andA1FI scenario combination.

Year	Pixel 5935[a] 0.33°N, 37.67°E, 1127 m Central Kenya		Year	Pixel 4240 0.50°S, 34.83°E, 1543 m Western Kenya	
	Mean yield (kg/ha)	Water stress[b]		Mean yield (kg/ha)	Water stress
2000	388	0.01	2000	1407	0.02
2010	474	0.00	2010	1447	0.03
2020	506	0.00	2020	1535	0.01
2030	619	0.00	2030	1558	0.01
2040	590	0.00	2040	1574	0.01
2050	786	0.00	2050	1630	0.06
Year	Pixel 6354 2.83°S, 38.33°E, 613 m Southern Kenya		Year	Pixel 6950 2.17°S, 39.33°E, 192 m Eastern Kenya	
	Mean yield (kg/ha)	Water stress		Mean yield (kg/ha)	Water stress
2000	2012	0.31	2000	771	0.47
2010	1873	0.35	2010	837	0.41
2020	1780	0.34	2020	759	0.58
2030	1616	0.40	2030	733	0.55
2040	1243	0.51	2040	606	0.61
2050	1052	0.55	2050	451	0.66

[a] Pixel locations: latitude, longitude, elevation.
[b] Water stress: A factor between 0 (no stress) and 1 (extreme stress) that accounts for water deficit effects on plant physiological processes (Ritchie, 1998).

both maize and beans is shown in Fig. 5. As noted above, the original triage for these simulations included all pixels where the agricultural suitability of the soil and the length of growing period were adequate to support the cultivation of maize, whether maize was grown there or not. To add more realism to this analysis, we masked out all pixels in Fig. 4 that were not classified as "cropland" using the data layer GLC 2000 (JRL, 2005). Scatter plots for this reduced number of "cropped and simulated" pixels are shown in Fig. 5. Taking the HadCM3 and A1FI climate model–scenario combination as an illustration, Fig. 5A plots the simulated mean maize yield changes between 2000 and 2050 against the average daily temperature for current conditions in each pixel (top panel) and against the pixel's elevation (bottom panel). Elevation itself is a reasonable predictor of yield change in maize ($r = 0.52$), while the average temperature is somewhat better ($r = -0.57$). The same scatter plots are shown for beans in Fig. 5B, and elevation ($r = 0.71$) and current average temperature ($r = -0.83$) are good predictors of simulated yield change to 2050.

For maize, yield benefits can generally be expected in cooler and/or higher elevation locations, up to current average temperatures of about 18–20 °C (Fig. 5A). For current average temperatures above this threshold, most pixels will see yield reductions, and some of these may be severe. For most pixels below about 1700 m elevation, reductions in maize yield are indicated, but not in all. In addition to the temperature effects on maize yield changes, there are also water effects. To illustrate, yields of maize for four pixels in different regions of Kenya are shown in Table 3, together with the summary water stress factor that is one of the outputs of the CERES-Maize model. This is a number between 0 (no stress) and 1 (extreme stress) that accounts for water deficit effects during the growing season on plant physiological processes such as leaf and stem extension growth and tillering (Ritchie, 1998). The top pair of pixels in Table 3, from central and western Kenya, show linear yield increases (statistically significant, as shown in the left panel of Fig. 4A). These pixels are located in medium-to-high altitude regions, and water stress plays almost no role in limiting maize yields in such regions. Current average temperatures for these two pixels (19.6 and 18.0 °C, respectively) are below the optimal range for tropical (30–35 °C) and tropical highland (20–30 °C) maize varieties (FAO, 1978), and so these are temperature-limited (and nitrogen-limited) environments. The bottom pair of pixels in Table 3, on the other hand, are from lower elevations in southern and eastern Kenya, with current average temperatures of 24.8 and 25.6 °C, respectively, and these show linear yield decreases (in the sense of Fig. 4A) to 2050. For these pixels, water stress plays an increasing role in limiting yields as temperatures increase. In general, decreases in plant-available soil water in these lower altitude environments are a common effect, although this is confounded by different soil types with different water holding capacities.

The relationship between bean yield changes and elevation is fairly strong, although not as strong as that with temperature (Fig. 5B). Results indicate that beans grown in almost all areas with elevations below 1000 m, and in many of the areas up to 1500 m, are likely to see yield reductions to 2050. The temperature threshold above which yield reductions are indicated is about 20–22 °C. This compares well with the temperature of 20 °C given by Boote et al. (1998) as being optimal for bean seed yield, simulated with an earlier version of the bean model used in this study. We investigated bean yields more closely in specific pixels that exhibited the linear and quadratic trends shown in Fig. 4B. For all of these pixels, there is comparatively little water stress during crop growth, using the same stress factor as in Table 3. This is to be expected, as the bean triage was made up of those pixels that are both classified as cropland and also have enough rainfall to allow secondary-season beans to be grown. Accordingly, the temperature response in the top panel of Fig. 5B explains much of the spatial and temporal variability in yield. In pixels where temperatures are projected to increase, and current temperatures are already above the 20–22 °C threshold, then yield decreases are experienced. In pixels where current temperatures are below the threshold, and do not increase substantially above the threshold by 2050, then bean yields increase. The pixels with quadratic yield decreases are characterised by average temperatures that start below the threshold in 2000 and move beyond it by 2050.

4. Discussion

The results above show that crop yield responses to the changing rainfall amounts and patterns and the generally increasing temperatures projected by GCMs are heterogeneous. They may vary by crop type, by location, and through time. Results also indicate that under the four GCM–scenario combinations considered, the aggregate production decreases are projected to be rather modest to 2050. These aggregate production changes, however, hide a large amount of variability, and under the higher emission scenario (A1FI), substantial maize and bean yield reductions can be expected in 50–70% of cropped pixels. At the same time, the highland areas in many parts will see increases in yield potential, although there may well be concomitant changes in the type, distribution and severity of crop diseases (which are not taken into account in these model runs) that will affect the yields that can be obtained under relatively low-input conditions.

A substantial part of this heterogeneity in yield response can be explained by temperature effects. In maize, at high altitudes, yields may increase as temperatures increase, but at most lower elevations, yield changes also depend on water balances, and many places will see increasing water stress in the maize crop, all other things being equal. For secondary-season beans, temperature-driven yield increases will occur at higher elevations or up to average temperatures of about 20–22 °C. Beyond these temperatures, yields will tend to decline. In terms of adaptation options, this simple characterisation suggests the need for more drought-tolerant maize varieties, coupled with management practices that can make the most of available rainfall (such as water harvesting, for example). For bean production, the results suggest that a shift in bean cropping to higher elevations may be appropriate. The generality of these results remains to be investigated in detail. However, given that average temperature is a reasonable predictor of the direction of possible yield impacts, and the relatively mountainous nature of the study region, it may be that local yield variations in regions with more homogeneous landscapes may be less marked than in East Africa.

The results do highlight the necessity of assessing impacts at the household level, however. Yield responses of maize and beans to climate change are different, but many smallholder systems in the region include a range of additional or different crop and livestock enterprises. In situations where maize stover is a key dry-season feed resource for cattle, for example, there are likely to be important implications in the reduction in maize biomass for livestock, in addition to the implications of reductions in maize grain for food security. While there are some places where maize yield reductions can be offset by increases in bean yields, there are other places where both suffer yield reductions. What are the implications of these impacts and their interactions with other farm and non-farm livelihood strategies on household income and food security? Further work is needed to assess the likely system-level impacts of climate change, to see where trade-offs are possible, where new opportunities present themselves, and where drastic action is needed if adaptation is to be effective.

Such considerations argue strongly in favour of relatively localised assessments of adaptation options. The specification and identification of large development domains can be very useful for broad-scale priority setting in agricultural research (see, for example, ASARECA, 2005; Thornton et al., 2007). Such work is, however, only the first step in a longer process to look in more detail at the physical system responses as well as at the heterogeneity of farm households with respect to socio-economic factors. The results above suggest that some of the heterogeneity in crop response to a changing climate, particularly the direction of yield changes, may be able to be addressed using relatively broad-scale temperature indicators. We are currently investigating the ways in which such information can be combined with more detailed household-level information, in the search for effective adaptation options in highly vulnerable places, many of which will require appropriate community- and national-level action.

The analysis presented here could be improved in several key respects. The science of climate modelling is continuing to develop quite rapidly, and there are various regional climate models that could be used for this study region (Olson et al., 2008). However, there is still considerable uncertainty associated with our understanding of what the local-level impacts of climate change are likely to be, in relation to the downscaling of coarse-resolution climate model output to the high spatial resolutions needed for effective adaptation work (Wilby, 2007). Choice of which GCMs to use, for example, would be considerably facilitated by validation studies, but comprehensive validation work on GCMs for African conditions is still needed.

It is likely that the extent of climate-related hazards is underestimated in the analysis above, because important extreme events such as droughts and flooding are not being directly taken into account. In addition, the analysis does not fully account for the fact that the variability of weather patterns in many places is increasing and with it the probability of extreme events and natural disasters occurring (Kasperson and Dow, 2005). Changing climate variability may have critical effects on several of the dimensions of food security; in addition to impacts on food availability, variability may strongly affect the stability of food supplies and vulnerable people's ability to access food at affordable prices (Schmidhuber and Tubiello, 2007). More work is needed on the variability issue.

A further refinement would be to adjust the triage of cropping pixels so that it bears more relation to the actual maize and bean cropping areas in the region. This could be done using crop distribution layers generated using the methods of You and Wood (2004), for example. These cropping areas could also be overlaid with detailed poverty and vulnerability data, to better identify those areas where impacts may be large and adaptive capacity low.

As noted above, there are also uncertainties associated with the crop model runs, to do with input data and model relationships themselves. For regional studies such as this, it is not easy to quantify how large these model-related errors might be—this warrants further work. In addition, there is rather more regional variation in varieties and crop management than we have included in these simulations, and more spatial information on farming systems and management regimes could usefully be incorporated into such analysis.

5. Conclusions

Information on the nature, extent and location of the impacts of climate change on households in Africa that are particularly dependent on natural resources for their livelihoods is crucial if appropriate adaptation options are to be designed and implemented to deal with changing crop and livestock production potential. These impacts may be highly variable across space and through time, as a result of the interactions between temperature increases and shifts in rainfall patterns and amount. In addition, there is enormous heterogeneity in households' access to resources, poverty levels, and ability to cope. While vulnerability and impact assessment work can usefully be guided by macro-level analyses, ultimately such work needs to be done at higher resolutions to allow effective pro-poor targeting of adaptation options. There is a considerable tension between the magnitude of the problems facing Sub-Saharan Africa and what can be done to help communities adapt that are appropriate to local conditions. This implies that the conventional wisdom of agricultural research for development as the producer of outputs that are applicable to large demand domains may need to be modified with another sort of wisdom that acknowledges the heterogeneity and complexity of the world and accepts that development domains may be geographically much smaller than previously anticipated—but at the same time this may result in research impacts being far better targeted.

It is becoming increasingly clear that a "business-as-usual" scenario for Africa is not an option. As Patz et al. (2005) note, the likely impacts of climate change present a global ethical challenge as well as a development and scientific challenge. Understanding what the likely impacts are likely to be on communities that have an inherently limited ability to adapt is still only one step in meeting these challenges, but there is still a considerable amount of work to do before our understanding is close to being adequate.

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