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East African food security as influenced by future climate change and land use change at local to regional scales

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Abstract Climate change impacts food production systems, particularly in locations with large, vulnerable populations. Elevated greenhouse gases (GHG), as well as land cover/land use change (LCLUC), can influence regional climate dynamics. Biophysical factors such as topography, soil type, and seasonal rainfall can strongly affect crop yields. We used a regional climate model derived from the Regional Atmospheric Modeling System (RAMS) to compare the effects of projected future GHG and future LCLUC on spatial variability of crop yields in East Africa.

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Crop yields were estimated with a process-based simulation model. The results suggest that: (1) GHG-influenced and LCLUC-influenced yield changes are highly heterogeneous across this region; (2) LCLUC effects are significant drivers of yield change; and (3) high spatial variability in yield is indicated for several key agricultural sub-regions of East Africa. Food production risk when considered at the household scale is largely dependent on the occurrence of extremes, so mean yield in some cases may be an incomplete predictor of risk. The broad range of projected crop yields reflects enormous variability in key parameters that underlie regional food security; hence, donor institutions' strategies and investments might benefit from considering the spatial distribution around mean impacts for a given region. Ultimately, global assessments of food security risk would benefit from including regional and local assessments of climate impacts on food production. This may be less of a consideration in other regions. This study supports the concept that LCLUC is a first-order factor in assessing food production risk.

1 Introduction

Assessing food production variability—a key element in food security risk—for developing nations is vital for policymakers, natural resource managers and non-government organizations (Parry 1990; Parry et al. 2004). Changes in climate due to enhanced greenhouse gases (GHG) are expected to have widespread impacts on food production in many regions (Lobell et al. 2008; Burke et al. 2009); indeed, GHG-driven climate change in East African region is likely underway now (Boko et al. 2007) impacting the livelihoods of millions of people. Climatic responses associated with increasing concentrations of GHG in East Africa are complex (Neilson and Drapek 1998) yet are generally expected to nudge the region towards a warmer and wetter state (Hulme et al. 2001).

Considerable research has recently focused on the potential impacts of climate change on food production (Parry et al. 1999; Livermore et al. 2003; Funk et al. 2005; Rosegrant et al. 2005; Tiffin and Xavier 2006; Thornton et al. 2009, among others). To date, many of these studies have been global in scope, often conducted using (1) empirical, linear models (e.g., Lobell and Field 2007) relating food production and climate variability and (2) input from climate models at coarse scales, usually from General Circulation Models (GCMs) either directly, downscaled, or aggregated (Lobell et al. 2008; Funk et al. 2008).

However, as many of these researchers have suggested, these approaches have several limitations. First, the scale and heterogeneity of climate impacts on food production may not adequately capture variability that is important in locations where technological capabilities and adaptations are limited and crops are grown for local subsistence. It is well known that GCMs (typically run at grid spacings of ~120 km or coarser) cannot simulate atmospheric dynamics associated with landscape variability. Second, impacts due to changes in land use and land cover are generally not explored. Third, atmospheric impacts caused by land cover and land use change (LCLUC) in parallel with changing greenhouse gas concentrations could also affect crop yields.

Recent efforts to prioritize climate change adaptations from the food security perspective are needed (e.g. Funk et al. 2008; Lobell et al. 2008) but lack important contributions from regional landscape heterogeneity that impact crop yields as they are assessed at fine resolutions. These complexities are evident in the strongly contrasting conclusions about East African food security as reported by Lobell et al. (2008)—who find East Africa insulated from increased risk—and Funk et al. (2008), who find "dangerous increases" Eastern and Southern Africa's food security risk. Thornton et al. (2009) argue strongly against using large spatially contiguous domains, such as those at national scales, to examine adaptations in regions with large variations in topography and average temperature.

Several physical features also contribute to East Africa's high local variability in climate: highly variable topography ranging from sea level along the coasts and the African Rift Valley to large continental volcanoes, expansive inland lakes (Anyah et al. 2006), complex seasonality associated with Indian Ocean influences (Black et al. 2003; Black 2005; Anyah and Semazzi 2007) and complex equatorial circulations (Ogallo 1989; Mutai and Ward 2000; Camberlin and Philippon 2002) that create conditions favorable for double cropping near the equator and single cropping at the northern and southern extents of the region. In this study we integrate fine resolution, spatially explicit crop-climate-land use models that incorporate the complex spatial heterogeneity of East African systems so that we can explore future climate change effects due to GHG and LCLUC on food production risk.

A second limitation of climate-food production studies conducted to date is that GCM-statistical climate-food production models miss important feedbacks that may result in systems where land use/cover change may alter local and/or regional climate dynamics. Several studies have demonstrated that Land Cover and Land Use Change (LCLUC) alter surface albedo which in turn may influence local and regional climate dynamics (Charney et al. 1977; Lofgren 1995; Semazzi and Song 2001). Thus LCLUC can exert an important influence on regional climate (Pielke et al. 2007; Anyah et al. 2006) and even the vegetation response to rainfall (Serneels et al. 2007), possibly with positive or negative feedback patterns. Besides GHG, LCLUC is also a primary driver of climate change at local to—in some cases—much larger scales (Feddema et al. 2005; Pielke et al. 2002; Maynard and Royer 2004). Land historically used for animal grazing in East Africa is being converted to cropland, and urban areas are expanding dramatically. These trends are expected to continue in the future (Olson et al. 2004; Mundia and Aniya 2005; Olson et al. 2007). Thus, LCLUC effects may moderate or amplify the GHG effects on climate change (Li and Mölders 2008). Anthropogenic effects include LCLUC.

Finally, crop yields are a function of many different biophysical factors (cf. Boyer 1982; Boote and Sinclair 2006; Hay and Porter 2006) including temperature, rainfall, length of season, and nutrient availability, among others. The interaction of these variables is known to be complex and likely nonlinear, and, as such, may not be well explained by linear statistical models. Relying on process-based models instead may help to better understand how complex climate patterns in addition to nutrient limitations may impact livelihoods of people in developing countries limited by technological solutions. Although pests, diseases and natural hazards are absent in most crop models, and there are concerns about reliability (Boote et al. 1996), crop models have been shown to be useful in understanding climate-crop interactions in many regions, including East Africa (e.g. Thornton et al. 2009).

Here, we attempt to address the shortcomings of coarse spatial resolution assessments of the impact of climate change on food security through high resolution studies of climate change, coupled to a process-based crop simulation model. Our hypothesis is that land use/cover change feedbacks may alter an assessment of future food production resulting singularly from GHG-induced climate change alone. In addition, we test whether or not finer and coarse resolution evaluations strongly differ. The work presented here is part of a larger project, the Climate-Land Interaction Project (Olson et al. 2007), aimed in part at understanding the relative variability and sensitivities of regional climate, crop yield, and human systems due to GHG forcings and LCLUC each of which operate in very different but important ways. Our objectives are threefold:

I. To test if spatially homogenous forcings (e.g. GHG forcings that show warming everywhere) can result in complex, heterogeneous crop responses as a result of spatial and temporal landscape heterogeneity.
II. To test whether spatial and temporal changes in temperature and precipitation due to LCLUC produce yield changes similar to GHG effects.
III. To examine how a process-based, high-resolution modeling approach differs from a coarse resolution statistical approach for estimating the impacts of climate change on food production risk.

2 Models and methods

This study focused on the East African countries of Kenya, Uganda, Tanzania, Burundi, and Rwanda (Fig. 1). This domain spans dramatic changes in elevation, annual rainfall, land cover, and soil type. As such, it is an appropriate location for examining the effects of landscape heterogeneity on climate variables and crop yield. Figure 1a shows average annual rainfall from the Worldclim data set (Hijmans et al. 2005), with population distributions (Fig. 1b) following a similar spatial distribution. Figure 1c is an estimate of maximum potential agricultural extent for maize that shows high fragmentation and heterogeneity. In contrast, projected changes in annual rainfall from the National Center for Atmospheric Research's Community Climate System Model (CCSM) 4.0 Scenario A1B from 2000–2009 to 2050–2059 (Fig. 1d) suggest a wetter trend but do not reflect complex local and mesoscale atmospheric features. The framework for examining the role of regional landscape heterogeneity on crop yields required inputs of land cover change and climate change as illustrated in Fig. 2. The elements of each model segment are described in more detail below.

2.1 Land cover/land use change modeling

We developed a hybrid land-use and land cover classification scheme (Torbick et al. 2006), in part, from Africover (2002) and with input from local African experts. Workshops of experts were used as one of the sources of information on future changes in land use; the basis for such future predictions was developed from a number of anticipated development programs, strategies, and other factors ranging from national to local scales. Landscapes for agriculture and urban were projected to 2050 using the artificial neural network and GIS based Land Transformation Model (Pijanowski et al. 2002, 2005, 2009) using regional data on roads, elevation, soils, rainfall, surface water and existing urban boundaries. Population data from the UN (2007) were used to scale the amount of required rainfed agriculture to 2050. The

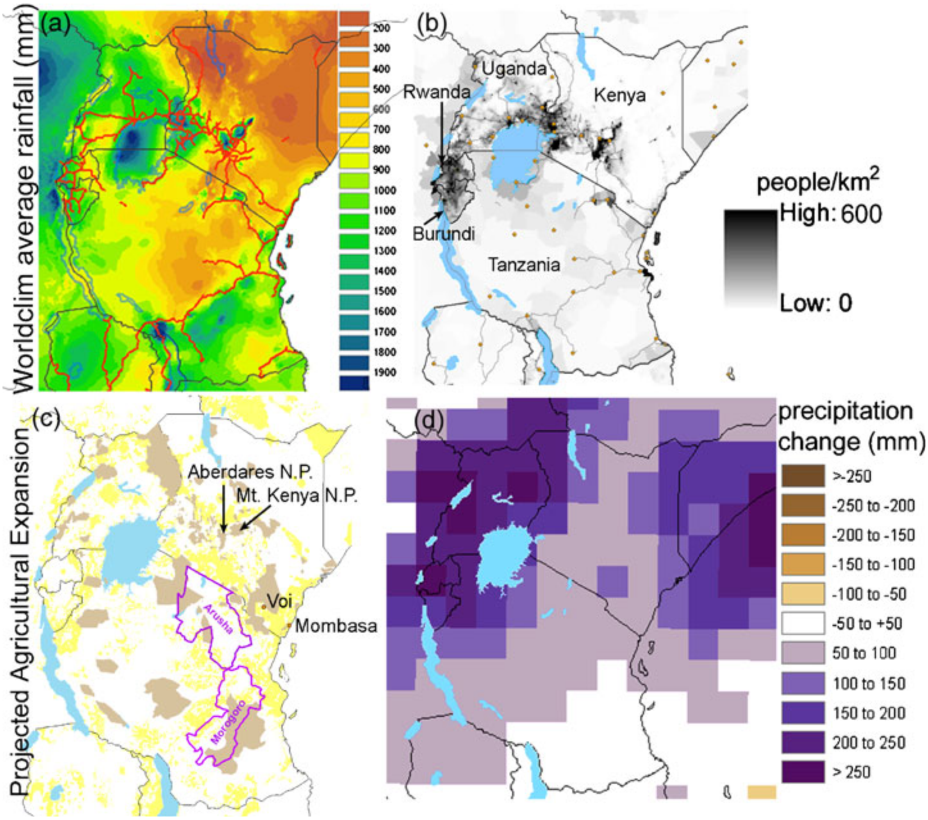
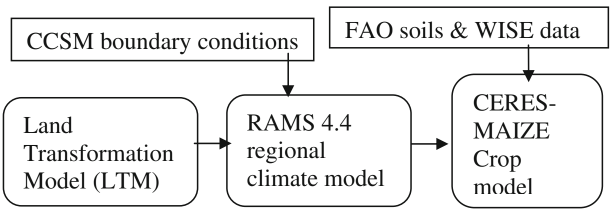


Fig. 1 Key spatial aspects in simulating current and future variability of food production in East Africa. **a** Average annual rainfall from Worldclim; **b** Population density from CIESIN (Center for International Earth Science Information Network); **c** LCLUC projection of agricultural expansion from 2000–2050 (*yellow*) and national parks (*brown*); **d** climate change projection of CCSM mean annual precipitation from 2000–2050 under the SRES A1B scenario

model was developed at 1 × 1 km resolution. Overall, we projected that East Africa would experience more than a doubling of total cropland by the year 2050. This is an extreme case, pursued to elicit a strong signal/noise ratio for understanding the scale of land change effects, and is not a likely outcome. This cropland expansion resulted in a decrease in broadleaf forests, open and closed savanna, shrublands and grassland. These were needed because of East Africa's bimodal phenology

Fig. 2 Flow diagram linking the land cover model, climate model, and crop model



for crops and other seasonal greening landscapes associated with "long rains" and "short rains" precipitation. We did not investigate subvarieties of LCLUC such as afforestation, pasture expansion, or silviculture. Increased agricultural expansion in some places (e.g. southern Kenya/Tsavo) is not realistic but is a consequence of extreme agricultural expansion; some small concessions like these were deemed acceptable for the purposes of a sensitivity experiment.

2.2 Regional atmospheric modeling

We used the Regional Atmospheric Modeling System (RAMS version 4.4; Cotton et al. 2003), a state-of-the-art limited-area atmospheric model. Our domain, 84 × 76 grid points, covered Kenya, Tanzania, Uganda, and several neighboring countries at a 36 km horizontal grid spacing and a vertical domain (32 levels) stretched to 32581 m above mean sea level, with the lowest level thickness 100 m. We employed the Kain–Fritsch convective parameterization (Kain and Fritsch 1993). Surface and vegetation dynamics were governed by the LEAF-2 sub-model (Walko et al. 2000), and land cover parameters like albedo, fractional cover, etc were linked to appropriate Global Land Classification (GLC) classes. Annual CO_2 concentrations and 6-hourly atmospheric boundary conditions for current and future climate were from the CCSM 3.0 model (Scenario A1B) for the decades 2000–2009 and 2050–2059 (Collins et al. 2006). The increased rainfall over this time span in CCSM's average annual precipitation is shown in Fig. 1d. We explored climate impacts attributable solely to GHG changes and to LCLUC. RAMS was thoroughly tested and evaluated with recent observed data using NCEP forcings. Regionally specific fractional cover and leaf area index (LAI) estimates developed from MODIS imagery (Wang and Yang 2007) were incorporated to improve the regional atmospheric model's performance (Moore et al. 2009). Since Indian Ocean temperatures may strongly influence coastal crop production (Funk et al. 2008), we included monthly CCSM sea surface temperatures from the same scenario into RAMS and included a sizeable portion of the Indian Ocean in our domain.

2.3 Crop yield modeling

To estimate the growth, development, and yield of crops under future and current climate and landscape conditions, we used a deterministic, process-based simulation model for maize. We used maize as a representative proxy food crop for the region. We used the CERES-Maize crop model (Ritchie et al. 1998) as currently implemented in version 4 of the Decision Support System for Agrotechnology Transfer (DSSAT; ICASA 2007) for all crop simulations. CERES-Maize requires daily precipitation, maximum and minimum temperatures, and incident solar radiation data. Daily time series of these were generated with MARKSIM (a statistical weather generator of daily data from monthly data; c.f. Jones and Thornton 2000) variables for historical and projected future time frames. We produced monthly mean data from RAMS outputs for the four decadal simulations in this study following the methods described by Jones and Thornton (2003). Soils data were derived from Food and Agricultural Organization soils map of world (FAO 1995) converted to a 30 arc-second grid which identifies all agriculturally suitable soils based on FAO soil unit ratings (FAO 1978) in the study region. We then used representative soils profiles from the International Soils Reference and Information Center's World Inventory of Soil Emission Potential Data base (Batjes and Bridges 1994) as modified by Gijsman et al. (2007) for each of the 18 km pixels in the domain where maize yield would be simulated. We assumed current representative smallholder cultural practices for maize cultivation; planting was assumed to occur automatically once the soil profile has received a thorough wetting at the start of the rainy seasons, and the crop was planted at a typical density of 3.7 plants/m^2. A nominal amount (5 kg/ha) of inorganic N was applied to the crop at planting. CERES-Maize does not account for the effects of pests, diseases and natural calamities such as hail. In this experiment, maize production was simulated in major production areas of other crops (e.g. rice, wheat, millet) as a proxy for productivity in general to assess yield sensitivity since maize is the primary food crop in East Africa. Although our results have this inherent inaccuracy of one-crop modeling and other crops may respond in different ways (c.f. Thornton et al. 2008), this method still allows for testing whether or not regional heterogeneity in GHG and LCLUC forcings has the potential to significantly affect crop production. As responsiveness of C4 crop yield to doubling of CO2 from 350 to 700 PPM was in the range of 4.2% increase under adequate soil moisture as summarized by Boote et al. (2010). In view of this marginal yield increase in C4 crops under adequate soil moisture due to CO2, we did not consider it in our simulation studies.

For comparing climate change effects on maize yield using a coarse resolution approach, we followed the technique of Lobell et al. (2008), as detailed in their supplemental online material. To briefly summarize that technique, we derived trends using the first-differences method (where year-to-year changes in modeled data are added to baseline observed data) from the same CCSM data used in our regional modeling to project climate (temperature and precipitation) to 2050. We also used the first-difference method for FAO yield data for Kenya, Tanzania, Rwanda, Burundi, and Uganda. FAO first-difference yield trends by country were then aggregated for 2050. In cases where actual values were needed instead of differences, we used CCSM changes superimposed on Worldclim climatology to tether the data to the real world. The point of the exercise was to test if finer time scales and spatial scales would give a significantly different average result in food yield, or if the yields would tend to be relatively insensitive to the scales of the models.

2.4 Experimental design

To evaluate the relative effects of GHG and LCLUC changes at fine resolution, we constructed four decade-long numerical land-climate simulation experiments:

Case 1 current GHG (CCSM 2000–2009), current land cover; "baseline simulation"
Case 2 elevated GHG (CCSM 2050–2059), current land cover
Case 3 current GHG (CCSM 2000–2009), expanded land cover
Case 4 elevated GHG (CCSM 2050–2059), expanded land cover

Case 1 provides a baseline for comparison under current CO_2 levels using ClipCover as the land surface. The two sensitivity experiments tested GHG impacts on yield for future (2050–2059) climate dynamics under elevated CO_2 levels (Case 2), LCLUC impacts on yield under current CO_2 levels (Case 3) and future LCLUC and GHG

Table 1 Local characteristics and yield influencing factors in selected SOIs

SOI exhibiting an effect	Characteristic of SOI	Yield influencing factor
SOI 1: Burundi	High elevation	Low Tmax
SOI 2: Western Tabora	High elevation	Low Tmax
SOI 3: SE Lake Victoria	Near Lake	Low rainfall
SOI 4: Morogoro	Sandy soils	Nitrogen stress
SOI 5: Central Uganda	High elevation (∼1200 m)	High Tmax
SOI 6: Kenya highlands	High elevation	Low Tmax
SOI 7: Longido/Nairobi	High elevation	Low Tmax
SOI 8: Kilimanjaro	High elevation	Low rainfall
SOI 9: Voi/Mombasa	Low elevation	Low rainfall
SOI 10: Lamu coast	Low elevation	High Tmax
SOI 11: Rwanda	High elevation	Cool; long CGD
SOI 12: South Uganda	Near lake	Cloudy
SOI 13: Central Uganda	High elevation	Low rainfall
SOI 14: S. Lake Victoria	Near lake	Cloudy
SOI 15: Pangani	High elevation	Short CGD
SOI 16: East Mt Kenya	High elevation	Low rainfall
SOI 17: Lamu Coast	Near water body	Hot; low rainfall
SOI 18: Iringa	High elevation	Short CGD
SOI 19: Morogoro	Sandy soils	High rainfall
SOI 20: Dar Es Salaam	Near water body	Low rainfall

High elevation is defined as >1,000 m; low elevation as <1,000 m; increased temperatures cause a decrease in growing season length, which can either increase yield (if currently cool) or decrease yield (if currently warm)

combined (Case 4). Daily minimum temperature (Tmin), maximum temperature (Tmax), and precipitation were input to the CERES-maize model. From these simulations were calculated changes in yield, as well as additional variables like crop growth duration (CGD), water stress and nitrogen stress. CGD is the length of time (days) between planting and physiological maturity. Differences in yield due to GHG effects (Case 2–Case 1) can be compared to estimates using a linear regression model to determine if coarse-resolution results are similar to fine-resolution results. Differences in yield due to LCLUC effects (Case 3–Case 1) will illustrate the possible magnitude of land change effects on climate. We hypothesize that land change effects have yield impacts of similar magnitude to GHG effects and ought to be included in assessments of food production risk. Regional models are suitable tools to identify areas of high sensitivity to GHG change and LCLUC. Since food security risk is influenced by extreme climate factors, we also selected 20 SOIs (Subregions Of Interest) displaying large changes in yield from each experiment to explore further for this experiment; Table 1 lists these SOIs and salient characteristics.

3 Results

In order to demonstrate the utility of an explicit spatial high-resolution analysis of climate change on maize yield, we illustrate yield changes associated with GHG and LCLUC in 20 selected SOIs, 10 SOIs for each climate forcing. These SOIs are the numbered colored polygons in Figs. 3 and 4 with SOI color indicating the main variable responsible for the change in annual yield. The SOIs were chosen to show

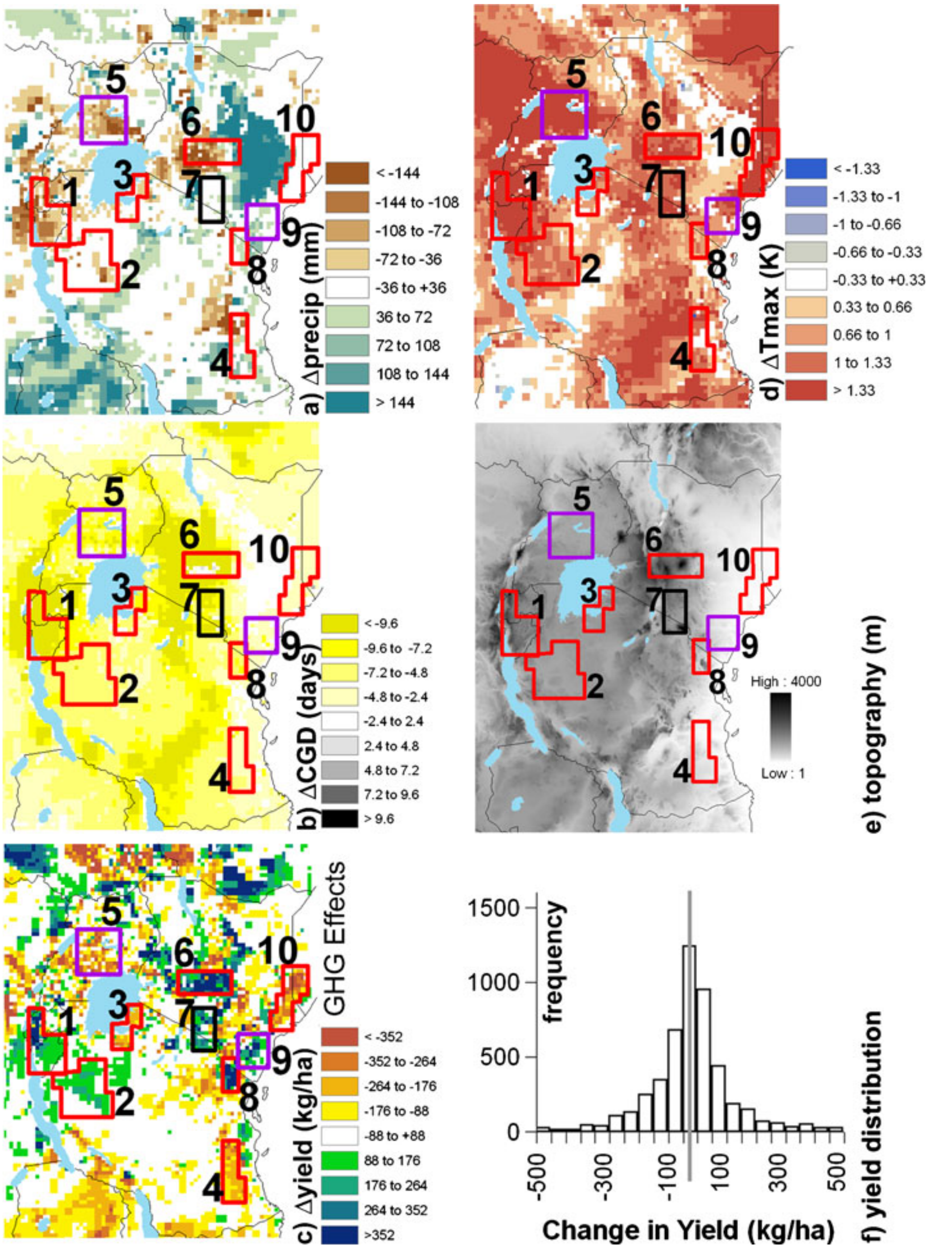


Fig. 3 GHG effects: average growing-season differences between 2000–2009 and 2050–2059 in: **a** mean precipitation, **b** crop growth duration (CGD), **c** yield change for the study area, **d** average maximum temperature, **e** topography, and **f** a histogram of yield change distribution for the 5 nations. Increments shown on **a** through **d** are half of one standard deviation (s/2) for each scale. Numbered Subregions Of Interest (SOIs) selected for high yield sensitivity are shown with colors indicating the driving climate factors behind the yield changes: *red* warmer, *blue* cooler, *purple* change in temperature and rainfall, *black* complex factors

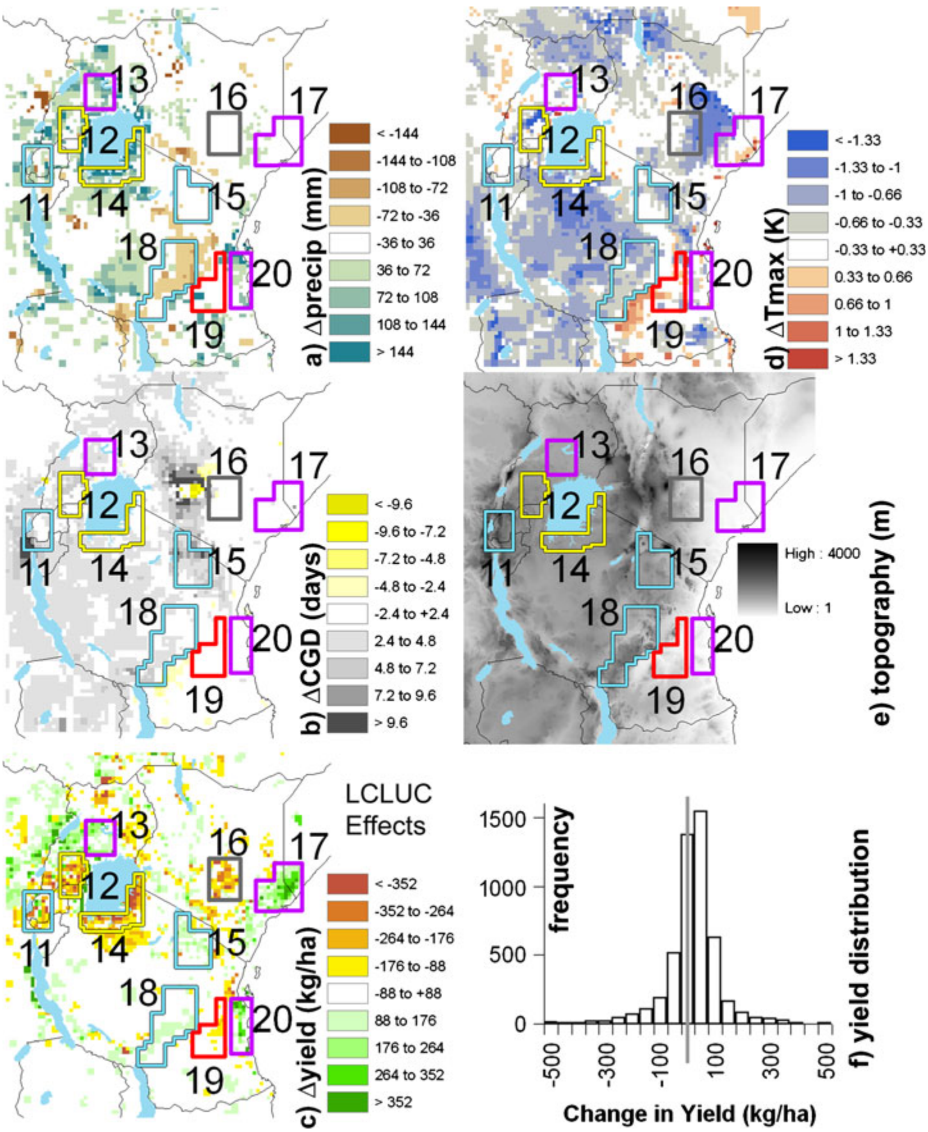


Fig. 4 LCLUC effects: average growing-season differences in: **a** mean precipitation, **b** CGD, **c** yield change for the study area, **d** average maximum temperature, **e** topography, and **f** histogram of yield change distribution for the 5 nations. Numbered Subregions Of Interest (SOIs) selected for high yield sensitivity are shown with colors indicating the driving climate factors behind the yield changes: *red* warmer, *blue* cooler, *yellow* decreased solar radiation, *purple* increased rainfall, *grey* complex factors

which yield changes that are sensitive to a variety of conditions of a regional nature. The overarching theme relating these 20 regions is heterogeneous yield response to spatially homogeneous/spatially uniform forcings caused by GHG or heterogeneous LCLUC forcings. That is, yield responses are strongly governed by regional and local features. Many of the selected areas are close to one another, yet they are associated with different yields, different climate forcings, or both. The color of the SOIs was assigned only if the change in the indicated climate variable changed more than the 10-year standard deviation. Thus, these yield-climate changes are not simply correlated, but infer causation.

3.1 Overview of spatial impacts of elevated GHG effects (Case 2)

Figure 3 shows changes in (a) growing season precipitation (PCP), (b) crop growth duration (CGD), (c) yield, and (d) average growing season Tmax between 2000 and 2050 under elevated GHG conditions using current land cover inputs (i.e., Case 2). These variables were selected to illustrate their main influences on maize yield. Topography in the study area is shown for reference in Fig. 3e. The PCP, Tmax and CGD exhibit a very strong correlation with elevation. Under elevated GHG, the East African highlands warm dramatically, accelerated crop development leading to decrease in CGD. Warming in other areas (e.g. Morogoro in SE Tanzania) was associated with smaller but important decreases in CGD, particularly in lower-altitude areas that are already warm. However, PCP and CGD in Fig. 3 are associated with complex and heterogeneous yield responses. Changes in PCP, Tmax, and CGD do not translate to direct and obvious changes in yield; rather, the yield changes show strong heterogeneity due to complex ways on the influence of driving variables.

Singly, PCP and CGD can affect yields significantly but together, their changes lead to heterogeneous responses in yield which is not easily deduced from broad features—for example, changes in PCP along with temperature change (influencing CGD) drive both increases (i.e. around Voi/Mombasa) and decreases (i.e. in central Uganda) in yield. In this example, increased precipitation near Voi/Mombasa alleviated water stress, thereby increasing simulated maize yields; however, in central Uganda a modest decrease in growing season precipitation together with elevated nighttime temperatures (which shorten the growing period) lead to a dramatic decline in yield; with an already short growing period, any water stress combined with a shortening of the growing period can rapidly shrink crucial phases of maize development. Similarly, increasing temperatures can also cause both yield declines as well as yield increases. Although warmer temperatures tend to contract the growing season—causing yield declines in hot regions (for example, Central Uganda)—warmer temperatures in the highland areas actually increase yields by improving plant function especially during the grain-filling phase (for example, the Aberdares and Mt. Kenya). Results shown in Fig. 3 indicate that complex yield changes are associated with spatially uniform/homogeneous climate drivers. The average yield is only part of the story; several locations show dramatic changes in yield. For example, the histogram in Fig. 3f shows a broad distribution of changes in yield occurring across the entire East African area plotted from values in 3(c) with a standard deviation of 176 kg/ha (this is given as an indication of domain-scale variability) which will be masked if only average yield is considered.

3.2 Overview of spatial impacts of LCLUC effects (Case 3)

Figure 4 shows changes between 2000 land cover and 2050 land cover in (a) PCP, (b) CGD, (c) yield, and (d) Tmax under LCLUC due to expansion of agriculture into existing savanna conditions (i.e., Case 3). Simulated LCLUC in savannah areas replaces moderate albedo grasses in the future that translate into higher albedo bare soil for part of the maize growing season, and similar albedo maize later in the growing season. This higher albedo under agricultural expansion leads to lower absorption of shortwave radiation that leads to slightly cooler maximum temperature as evident in Fig. 4d. These cooler maximum temperatures increase the growing season and CGD. Topography is again shown in 4(e) for reference. Figure 4f shows the distribution of yield change from 4(c; The gray vertical line is zero). The LCLUC effects, on average, produced yield changes at a magnitude similar to those of GHG effects (compare to Fig. 3c; see also Fig. 5d), but the climate changes associated with LCLUC are more disaggregated and concentrated than GHG effects. The GHG effects dominate extremes in yield change.

Although more obvious, these results show that heterogeneous changes in land cover can cause heterogeneous maize yield changes. For example, SOI 15 and SOI 16 in Fig. 4 were both areas of cooler Tmax with time but had opposite responses in yield change. A strong relationship with topography—both with elevation and proximity to water bodies—is evident with the climate variables, although PCP changes are more muted and influenced by proximity to water bodies (leading to increased rainfall) or in steppe areas like Arusha in SOI 15 (decreased rainfall). Similarly, CGD increases are closely linked to the highland areas but show more muted responses elsewhere. Processed-based modeling is capable of capturing these relationships. As a second example, the opposite yields in SOI 12 and SOI 13 are driven by differences in solar radiation and rainfall despite both areas receiving similar increases in rainfall. Again, the changes in yield respond differently in different areas despite a similar climate forcing. The model results in Fig. 4c show that in some cases, large and broad climate perturbations (e.g. Western Tanzania) led to no significant changes in yield. Often, the model shows rainfall changes being driven by changes in convection, which has been observed elsewhere (e.g. Allard and Carleton 2010).

3.3 Overview of combined GHG and LCLUC effects

GHG effects on climate dwarf LCLUC effects across much of the domain, and that dominance extends to average yields in Case 4. Figure 5a–c shows the yield changes due to individual and combined effects, given here in percentage terms. Individual climate factors for Case 4 (not shown) are quite similar to Case 2 climate factors shown in Fig. 3. Although the LCLUC effects on climate and yield are generally smaller, they are not negligible. These areas are all important agricultural areas, and yield changes there may have a large impact on food security. Although GHG effects are clearly larger than LCLUC effects, LCLUC effects are not second-order or negligible. Figure 5d shows the ratio of yield changes (ratio = LCLUC/GHG) to illustrate where LCLUC causes a similar or larger impact on yields than GHG; a ratio of one would indicate that LCLUC and GHG have an equal impact on change in yield. Areas with marginal yields for Case 1 were omitted from the ratio, as were small values for GHG effects to avoid curiously small denominators. Both green and yellow represent areas where LCLUC impacts are larger than GHG impacts (i.e. $|\text{ratio}| > 1$). Green is used for increased yield in an LCLUC-dominated area; yellow is used for *decreased* yield in an LCLUC-dominated area. Grey represents areas where LCLUC impacts are less than GHG effects (i.e. $|\text{ratio}| < 1$). For

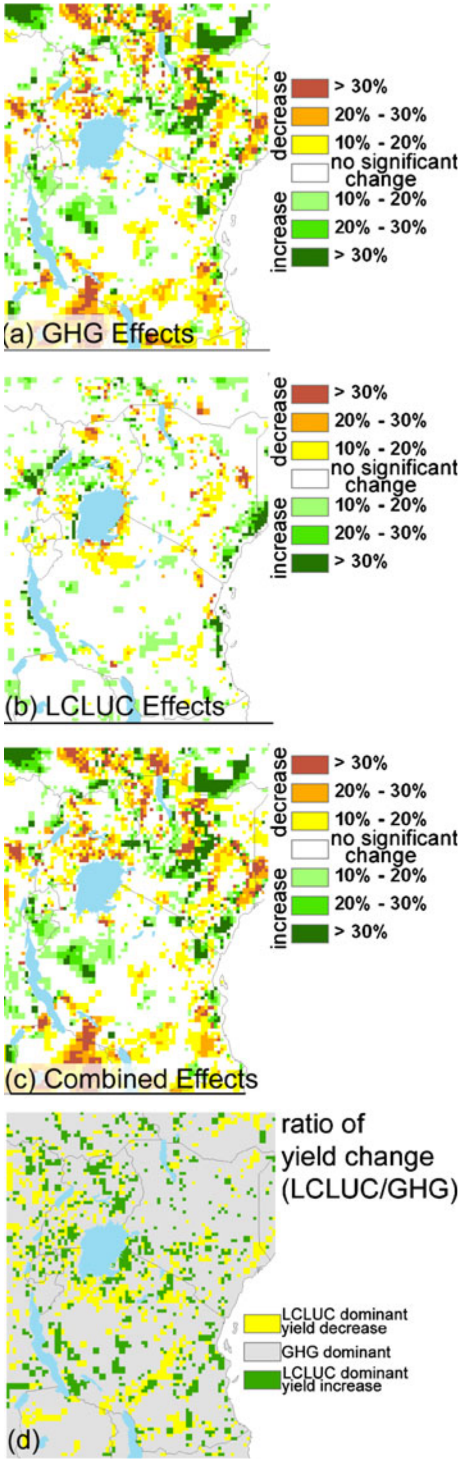


Fig. 5 Percentage change in maize yield compared to the baseline simulation (Case 1) for: **a** GHG effects/Case 2, **b** LCLUC effects/Case 3, and **c** Combined effects/Case 4. **d** Yield change of Case 4–Case 2, which shows the role of LCLUC in perturbing GHG effects

Fig. 5d, approximately 30% of the domain is not dominated by GHG effects alone; this demonstrates that LCLUC factors are of first-order consideration for food production.

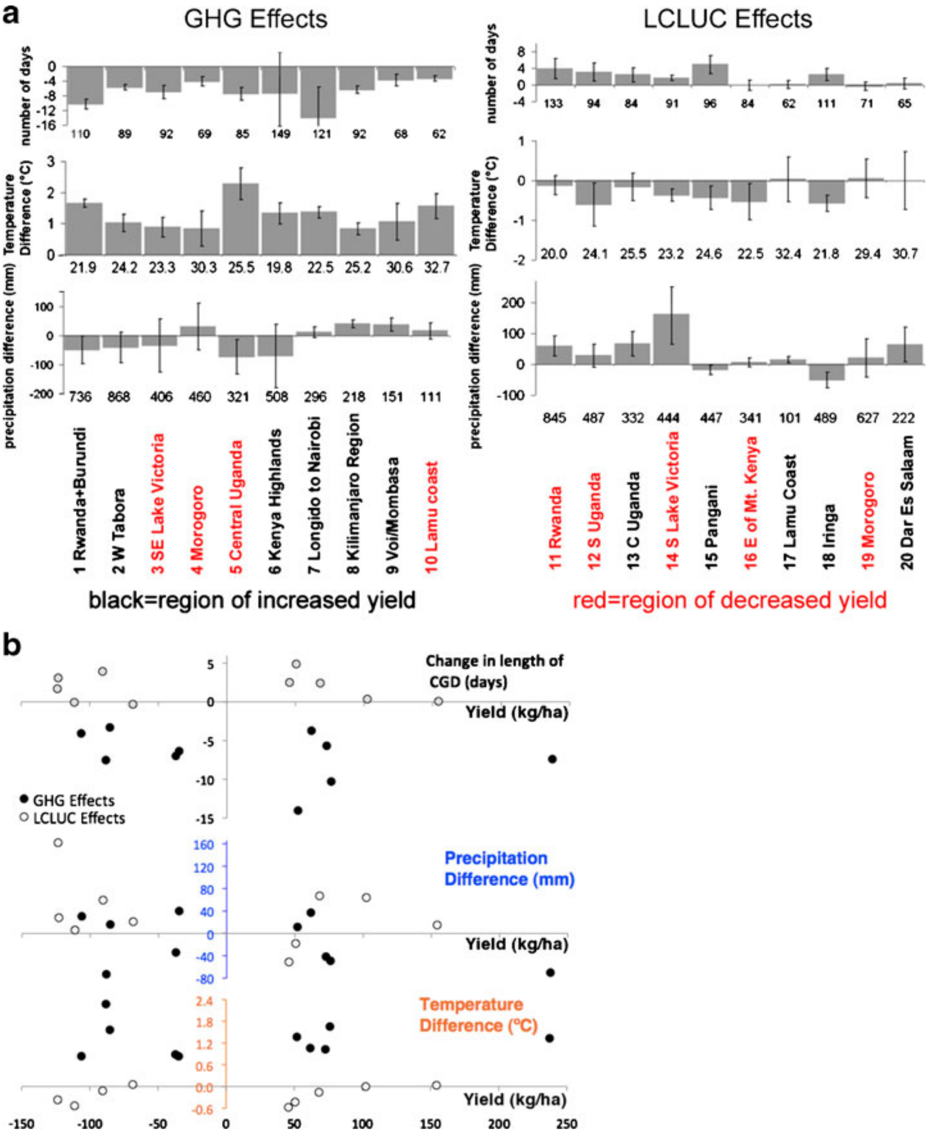


Fig. 6 **a** Changes in selected climate variables for the 10 GHG regions (*left*) and the 10 LCLUC regions (*right*) outlined in Figs. 3 and 4. Values along the bottom of each graph give average values from the baseline simulations to help understand the importance of the change. *Red* decreasing yield SOI, *black* increasing yield SOI. Each region has at least 30 pixels. **b** The same data re-plotted to show the lack of correlation between the individual climate forcings and the simulated yields

3.4 Complex drivers of yield change

Many different yield changes occur despite similar climate forcings, as shown in Fig. 6a. For example, PCP in much of the highland areas decreases, leading to regions of both increased and decreased yield. This is illustrated in Fig. 6a, left panel, where SOIs 2, 5, and 6 all show decreased precipitation, though SOI 5 has a yield decrease and SOIs 2 and 6 show yield increases. These contrary results occur because of other factors—such as temperature increases in the case of Central Uganda. Similarly, at lower elevations, central-eastern Kenya (semi-arid SOI 16) and SW Tanzania (extremely rainy near the Zambia border, not an SOI) show opposite responses in yield despite enhanced rainfall in both locations. Changes in Tmax and CGD are very strongly correlated, but these are both shown because in some cases Tmax may change significantly while CGD does not (e.g. SOI 16) or vice versa (SOIs 11 and 13).

In some instances, seemingly contrary results (e.g. SOI 8: less rainfall, but a yield increase) occur for the same selected regions. This occurs when averages over the growing season do not reflect daily differences in rainfall intensity, cloudiness, or other factors. For our first example, under LCLUC effects, Southern and Central Uganda (Fig. 6a, SOIs 12 and 13) both receive increased rainfall and are near one another. However, the yield changes are opposite in sign, and the increased yield in Central Uganda is due to additional rainfall while the decline in yield to the south is due to decreased temperature and decreased solar radiation (not shown). Under GHG effects, our second example, a similar counterintuitive response is also evident for GHG in SOIs 9 and 10 which both undergo large increases in Tmax. SOI 9 receives a small amount more rainfall (and at timely intervals during the growing season, while SOI 10 receives no significant additional rainfall, thus reaching high levels of water stress and high temperatures stress. Curiously, a large increase in rainfall between SOIs 6 and 10 (Fig. 6 shows a large decrease in PCP in SOI 6 and no change in SOI 10) leads to different yield changes—an increase in higher altitudes, a mild decrease in lower altitudes (see SOI 10 in Fig. 4a—already marginal), and no change in others. This reiterates that even modest simulations of food production can display a variety of counterintuitive outcomes that depend sensitively on local and regional conditions.

Figure 6b is a further illustration that these variables show very low correlation at regional scales. The horizontal axis is the same for all three panels. Although distinct differences are evident between GHG and LCLUC effects, their relative forcings show no evident pattern.

3.5 Coarse-resolution versus fine-resolution approach/assessment

One of objectives in this study was to compare a coarse-resolution assessment to a fine-resolution assessment (Fig. 7) for East Africa. For the sake of comparison, this figure shows regional average change in yield derived from a coarse-resolution linear approach (done by reproducing crop yield estimates forced by GCM data (see Methods, Section 2.3 for details) compared to a dynamically downscaled regional climate model coupled to a process-based crop simulation model. The linear regression model R^2 was 0.24; while the regression coefficients were 3.81 for temperature, 0.0005 for rainfall, and 5×10^{-5} for the cross-term. Each bar represents the average

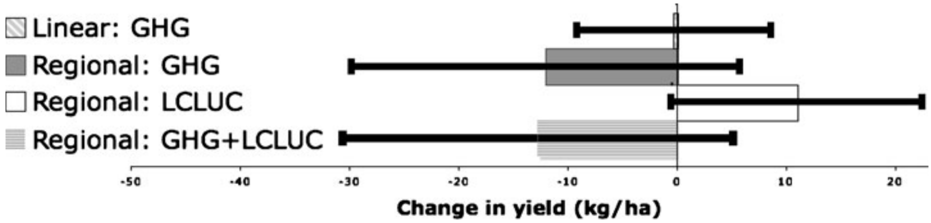


Fig. 7 Ranges of yield change variability comparing a linear statistical model versus integrated models that compare climate and land cover/use change. The *top bar graph* shows estimated GHG-driven yield change with a simple regression model; the *middle bar graph* shows an opposite response using regional process-based models; the *third bar graph* shows the effects of LCLUC using regional process-based models. Standard errors are (*top*) ±8.9 kg/ha, (*second*) ±17.8 kg/ha, (*third*) ±11.5 kg/ha, and (*bottom*) ±17.9 kg/ha

regional yield change from current to future conditions using the same GCM data. The error bars represent the standard errors for each ten-year sample. These two approaches are substantially different. That is, the coarse approach aggregates yield (or yield response) over large areas, assumes linear relationships between climate and yield, and tracks only the average values for the region. The fine-resolution approach is disaggregated to respond to spatial variability, explicitly calculates the nonlinear climate–yield relationships, and keeps an account of spatial variability in addition to national average yield values. In order to compare the regional simulations with the coarse model results, we aggregated finer resolution assessment results of this study to the national level, and compared the statistics of several countries together: Kenya + Tanzania + Rwanda + Burundi + Uganda.

As a result of these substantially different inputs and methods, the finer-resolution GHG forcings and LCLUC forcings show different responses (the lower three bar graphs) from one another and from the coarse-resolution approach (Fig. 7). The finer resolution approach of modeling of GHG effects produced a yield difference standard deviation of 176 kg/ha (see Fig. 3f). Using the linear regression model as described in the Methods section, the yield difference standard deviation due to GHG would be 79 kg/ha—much smaller. Standard deviation and standard error are key measures of variability; a lack of change in mean yields does not imply a lack of change in yield variability. Here, the mean values are different (though statistically no different from zero)—but more importantly, the variability is much greater for the regional experiments and better captures climate change effects than the coarse-resolution approach (c.f. Thornton et al. 2009). Furthermore, aggregate expressions of yield change, in and of themselves (as in Fig. 7), are an incomplete description of yield changes and food risk; the spatial distribution and causative factors are also needed.

4 Discussion

This paper illustrates three important factors that need to be considered when making estimates of food production and risk due to future climate change. First, heterogeneous responses in yield can result from homogeneous climate drivers.

Second, LCLUC can also significantly influence crop yield at a scale similar to GHG effects. Third, a process-based fine-resolution framework can produce different distributions of variability in yield. This third point has been shown before (e.g. Jones and Thornton 2003; Thornton et al. 2009) but it is an important element in determining risk—i.e., regional variability (and thus risk) is large and may be masked at coarse resolution. Since food production risk is primarily associated with the occurrence of extremes, a high-resolution approach exhibits much higher sensitivity to yield changes as well as much higher spatial variability.

We used a process-based deterministic crop model, driven by a deterministic regional climate model, with inclusion of two drivers of climate change. With models that incorporate process-based factors, some explanatory power is gained by looking at aspects like water stress or nitrogen stress, which are taken into account by the crop-climate model. This crop model is deterministic; thus a change in yield can be traced directly to the change in a climate variable (or variables) that caused the yield change. This is also true for linear regression models, but processed-based models allow us to examine causality as well as complex, nonlinear factors. For many climate changes, smaller percentage impacts (e.g. those less than 10%) are simply not significant, particularly given all the possible errors involved. Even large changes in climate forcings—like a large increase in rainfall—may not be significant because of other factors (e.g. sandy soils or hot growing-season temperatures) that may be poorly handled by crop models. However, some significant changes do emerge even though the aggregate histograms in Figs. 3f and 4f center about zero. Comparing yield changes in Figs. 3f and 4f, greater food production variability was obtained using this higher resolution approach that would not be evident using data aggregated to the national level (see Fig. 7). Furthermore, Fig. 7 only displays spatial variability, not inter-annual variability. The strength of a fine-resolution/regional approach is ultimately in its ability to identify regions and physical causes for elevated food production risk via localized trends in yield change, which could lead to more effective use of donor investments for alleviating hunger and poverty.

How much trust can be placed in these model results? Both the crop and climate models are limited in their abilities to reflect reality. These models are limited by the quality of the input data, their accuracies in parameterizing complex processes like turbulence or the grin-filling stage, and their outright non-use of factors like pests or subgrid-scale phenomena. Heterogeneity of our model responses is complicated too; since no spatially explicit data on crop yields in east Africa are available, it is very difficult to validate crop model yields except at aggregated (i.e., national) levels. Even then, national estimates in Uganda, Kenya and Tanzania are often based on very rough estimates for yields in more rural areas. Without good ground truth, it is quite possible that our model results could over-estimate the heterogeneity of the responses to the LCLUC and GHG forcings. However, these are process-based models. They have been built carefully and validated against ground truth in many locations. We can examine the reasons and causality for a change in yield. For example, if we examined maize yield near Mwanza, we can check the model to see that nitrogen stress is the reason for a given decline in the model. Thus, while the response heterogeneity could be overestimated, the responses are not "noise" or just a side effect of simple models forced by strong anomalies. The forcings are within reasonable range of actual weather values and they are broadly consistent with observed historical trends. The historical crop responses fall well within expected ranges for real maize yields in east Africa. Thus, the changes we see in the modeled yields broadly reflect possible changes caused by climate forcings from LCLUC and GHG. For further information on the limitations of these models, several model intercomparison projects (MIPs) that include RAMS are available that describe model shortcomings. For CERES, validation can be found in numerous publications including Jones et al. (2003).

These model projections are intended mainly to illustrate variability and the importance of LCLUC as a driver of yield change. Since the projections are peculiar to one particular future landscape and scenario, the specific patterns we find should not be used to plan adaptations. Rather, they can inform how we plan adaptations—by encouraging more spatially explicit measurements of climate trends in specific areas, by suggesting several pilot programs for different crop breeds, and by promoting more local (in-country) modeling of crop yields by scientists who are familiar with local trends, local breeds, and habits of local agriculture. The projections shown here do not have sufficient resolution or generalization to plan adaptations, but they do point to areas that may show climate sensitivity; these areas would benefit from more climate and crop monitoring.

We have demonstrated that high-resolution spatial characteristics (such as sandy soils, nitrogen inputs, etc) exert important constraints in understanding the system's climate shifts and resultant yield changes. These factors can play different roles under GHG forcings or LCLUC forcings. The context of projected yield change must be examined as well—for example, valuable cash crops like coffee and tea should not (and certainly will not) be abandoned in Kenya's highland areas merely because conditions are more suitable for a cereal crop. In the Kenya highlands, even a projected gain (of maize yield) is not necessarily enough to transform the agricultural systems there because farmers decide land use in a context of culture, economic forces, and sophisticated relationships within their societies. While our extreme case of massive LCLUC here ignored some socioeconomic constraints related to major protected areas (important for tourism), it was done to illustrate the sensitivity of certain areas.

Since our results show complex impacts, the ability of livelihood systems to adapt or mitigate climate change effects may depend on the character of the drivers most influential for the locality (e.g. Table 1) and the adaptive capacity of the human system in question. Thoughtful land use and land management could thus play a major role in coping with climate change and adapting human livelihood systems, such as decentralized ranching and shifts in crop production areas. We only investigated consequences for maize production; other impacts on human systems (e.g. water availability, livestock health, invasive species) may also reflect climate shocks with similar GHG, LCLUC, or coupled spatial responses. These are indicative of complex features and responses of the complex natural-human systems, warranting further study of savanna ecosystems.

Diffenbaugh et al. (2005) state "consideration of fine-scale processes is critical for accurate assessment of local- and regional-scale vulnerability to climate change." Our analysis reinforces this perspective. Addressing Objective II, we also show that future LCLUC is a first-order driver of yield change via modification of the surface energy budget (e.g. Seneviratne et al. 2006). Our results indicate that (1) crop yield can exhibit complex responses to broadly homogeneous climate forcings like elevated GHG influences, and (2) LCLUC-driven climate forcings are capable of driving yield changes similar in magnitude to GHG that also exhibit highly complex heterogeneous responses. The magnitude of the changes in yield modeled here are quite high, suggesting that LCLUC plays a critical role in food production risk. The choice of regional climate model can also strongly affect the outcomes of such studies, and this is an important element to consider in developing these types of studies (Oettli et al. 2011).

Quantifying the variability in yield plays a critical role in the assessment of food production risk—in turn a critical aspect of food security risk. From the perspective of sustainability and understanding agricultural productivity, it is important that donor institutions consider matters of land use, scale/resolution, heterogeneity, and representativeness when evaluating comparisons of responses in different regions or continents to climate change. Despite some drawbacks, process-based crop models might be used when appropriate to examine variability in regional food security risk and to understand which climate factors, including LCLUC, are of paramount importance to the farmers on the ground. Finally, and perhaps most importantly, we recommend that climate impacts of LCLUC be considered as a primary driver of food production risk.

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