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# The potential impacts of climate change on maize production in Africa and Latin America in 2055

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**Abstract**

The impacts of climate change on agriculture may add significantly to the development challenges of ensuring food security and reducing poverty. We show the possible impacts on maize production in Africa and Latin America to 2055, using high-resolution methods to generate characteristic daily weather data for driving a detailed simulation model of the maize crop. Although the results indicate an overall reduction of only 10% in maize production to 2055, equivalent to losses of $2 billion per year, the aggregate results hide enormous variability: areas can be identified where maize yields may change substantially. Climate change urgently needs to be assessed at the level of the household, so that poor and vulnerable people dependent on agriculture can be appropriately targeted in research and development activities whose object is poverty alleviation.


*Keywords:* DSSAT; MarkSim; CERES maize; Crop modelling; Risk; Poverty

## 1. Introduction

Nearly half of the world's population (2.9 billion people) lives on less than $2 per day (World Bank, 2001). Already, 800 million people are malnourished and food production has to double in the next 35 years to meet future needs (Watson, 2001). These advances have to be achieved in the face of climate change, the recent consensus being that it will affect our lives in many ways (IPCC, 2001a). The impacts on people's livelihoods will be greatest in the tropics and subtropics, and particularly in Africa, mainly because many poor smallholders depend on agriculture and have few alternatives (IPCC, 2001b). Such considerations pose considerable challenges for development, food security and poverty alleviation and raise many questions. What may be the impacts of climate change at local as well as at national and continental levels? How will they add to the development challenge? Which research and development activities are likely to help, and how can they be appropriately targeted?

Uncertainty is rife when addressing such questions but methods based on geographic information systems and agro-ecological zoning can provide broad-brush approximations of the expected effects (Openshaw and Turner, 1998; Fischer et al., 2001). Process-based models can give a more precise estimate of expected crop response (Rosenzweig and Hillel, 1998; Rosenzweig and Iglesias, 2001) but predictions may be based on extrapolations from relatively few point estimates. In a pilot study (Jones and Thornton, 2001), we tested the use of a process model for mapping the impact of climate change in an area of south-east Africa. The method was based on a weather generator that operates on climate surfaces. Using the output of a global circulation model (GCM), we generated surfaces that are characteristic of predicted climate to 2055. We then produced daily weather data that are characteristic of the modified climate surfaces to drive a dynamic, process-based crop model. We ran simulations of maize and pasture growth for combinations of climate and soil types in the study window and compared yield distributions now and five decades in the future.

In this paper, we extend these methods to all of Africa and Latin America, where smallholder rainfed maize production is feasible. The method allows impact assessment to be carried out at relatively high resolution, because it generates results at a sampling density sufficient to delineate detailed local variations in crop response. We focus on maize because of the importance of this crop to

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smallholders in Africa and Latin America, particularly to poor livestock keepers in the mixed crop–livestock systems so prevalent in these continents.

There may be as many as 40 million poor livestock keepers in the mixed systems of Latin America and 130 million in those of sub-Saharan Africa, and a substantial proportion of these people depend on maize to a large extent (Thornton et al., 2002). The analysis described below allows the identification of areas where yield changes are predicted to be very large. The implications may be profound for householders located in such places, for whom the maize crop is of critical importance to food security and income generation. This highlights the need for assessing the impacts of climate change at the level of the agricultural household using high-resolution methods. Although the case study presented here falls far short of the type of comprehensive systems analyses that are required (in addition, we illustrate the method using outputs from only one GCM), we believe that the methods outlined, when linked to appropriate household models, could go a long way towards more appropriate targeting of agricultural research and development activities for poor and vulnerable people, in response to possible climate change.

## 2. Methods

We have developed and extensively tested a third-order Markov rainfall model (Jones and Thornton, 1993). To simulate the variance of monthly and annual rainfall for sites in the tropics and subtropics, the rainfall generator carries 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). The model can thus 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). The model, MarkSim, 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 10 years of record over the period 1920–1990. MarkSim estimates monthly solar radiation using the model of Donatelli and Campbell (1997). To derive climate surfaces for Latin America and for Africa for 2055 (and subsequently daily weather data characteristic of the predicted climate normals), we accessed the Intergovernmental Panel on Climate Change Data Distribution Centre on the worldwide Web (http://ipcc-ddc.cru.uea.ac.uk/). We used an experiment conducted at the Hadley Centre, East Anglia, using the Unified Model (Cullen, 1993). The model, HadCM2, has a spatial resolution of $2.5^\circ \times 3.75^\circ$ (latitude by longitude). Monthly mean values of maximum and minimum temperatures and precipitation for the periods 2010–2039 and 2040–2069 were interpolated, using inverse-square distance weighting, to the same grid as MarkSim, a resolution of 10 min of arc.

To estimate the likely maize-growing areas in Africa and Latin America, we made a sequential triage of the climate pixels. We eliminated those pixels with growing seasons shorter than 60 days and growing season temperatures below 10°C. Next, we overlaid the remaining pixels with the global land-cover characteristics database (Loveland et al., 2000), as modified by Wood et al. (2000). The latter authors identified a class of pixels with no cultivation. They aggregated pixels with small amounts of cultivated area into a class with less than 30% of the area cultivated. To concentrate our analysis on more probable maize areas, we eliminated these two classes, along with pixels in protected areas. We then converted the Food and Agriculture Organization soils map of the world coverage (FAO, 1995) to a 30 arcsec grid and identified all soils with agricultural potential in each climate pixel. This resulted in some 58,000 pixels in Africa and Latin America, with an average of about 3.5 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). For this exercise we assume current varieties and cultural practices. This, of course, will not be the case as plant breeding and agronomic research will not stand still; however, it is intended to give us a baseline of what would happen if nothing changed in these factors. CERES-maize runs with a daily time step and requires daily weather data (maximum and minimum temperature, solar radiation, and rainfall). It calculates crop phasic and morphological development using temperature, day length and genetic characteristics. Water and nitrogen balance submodels provide feedback that influences the developmental and growth processes (Ritchie et al., 1998). Built in North America, CERES-maize has been widely used in Africa (Muchena and Iglesias, 1995; Thornton et al., 1995; Wafula, 1995; Schulze, 2000) and Latin America (Bowen et al., 1992; Hansen et al., 1997; Magrin et al., 1997). We used four generic varieties with a wide range of requirements for growing degree days calculated using a base of 8°C (Ritchie et al., 1998). Planting dates for each pixel–soil type combination were estimated using a simple water balance model on a smoothed daily rainfall record for each climate scenario. The growing season was defined to start after 5 consecutive days with volumetric soil water content in the top 100 cm above 70%. The end of the season was deemed to occur when soil water content fell below 50% for 8 consecutive days. The resultant number of growing degree days was calculated and used to select one of the four maize varieties that best matched thermal time requirements. The simulated crops were sown at planting densities typical of smallholder maize production systems that are hill-planted and rainfed, in the tropics. The varieties were planted at a density of 3.7 plants/m$^2$, with 50 kg/ha of mineral N distributed through the soil profile. For all soils, 10 kg/ha of inorganic N was applied to the crop at planting. The planting was assumed to be a maize monocrop and the model was reinitialized at the start of each run to make the runs independent.

We made a qualitative assessment of the soil types in the maize areas of Africa and Latin America, based on the soil unit ratings in FAO (1978), as to their agricultural suitability for maize production: class 1, unsuitable; class 2, moderately suitable; and class 3, highly suitable. We assembled representative profiles from the International Soils Reference and Information Center's World Inventory of Soil Emission Potentials (WISE) database (Batjes and Bridges, 1994) for each of the soils in classes 2 and 3, with additional inputs from the soil profile database holdings at CIAT and ILRI. Some soil profiles in the databases had values for water holding capacities, and these were used where possible. For other profiles with no such data, soil water-holding capacities were estimated from soil texture (Ritchie, 1998). Soil carbon was estimated as the modal value in the soil databases.

We carried out 20 replicates (different weather years) for the following three scenarios: the baseline, using 1990 climate normals; the "2025" scenario, using climate normals for the period 2010–2039; and the "2055" scenario, using climate normals for 2040–2069. We report on the baseline and 2055 scenarios in the next section.

To calculate yield probabilities, we took the yields from each of the 20 runs on each soil in the pixel, multiplied the instances by the percentage frequencies of each soil in the pixel and sorted the resultant list in the ascending order of yield. This yielded a distribution-free cumulative probability table that was read off to obtain the probability of obtaining any given yield.

## 3. Results

The predominant difference between the baseline and 2055 scenarios in both continents appears to be a reduction in yield (Fig. 1). However, the maps also reveal some areas where yields are predicted to increase,

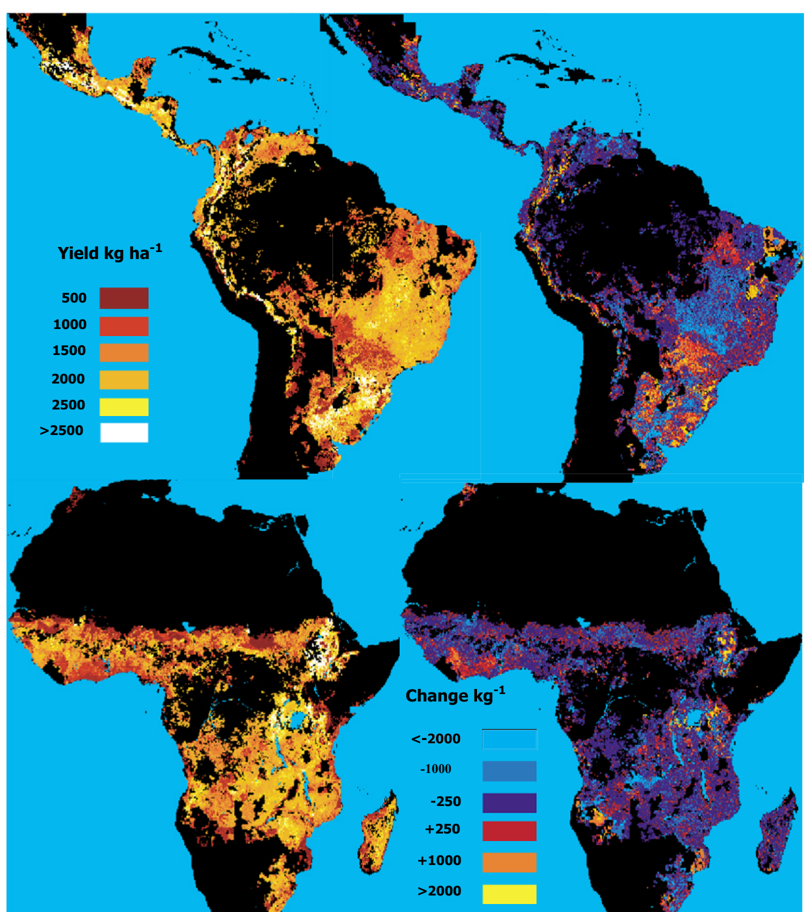


Fig. 1. Simulated maize yields (baseline) and changes to 2055 for Africa and Latin America.

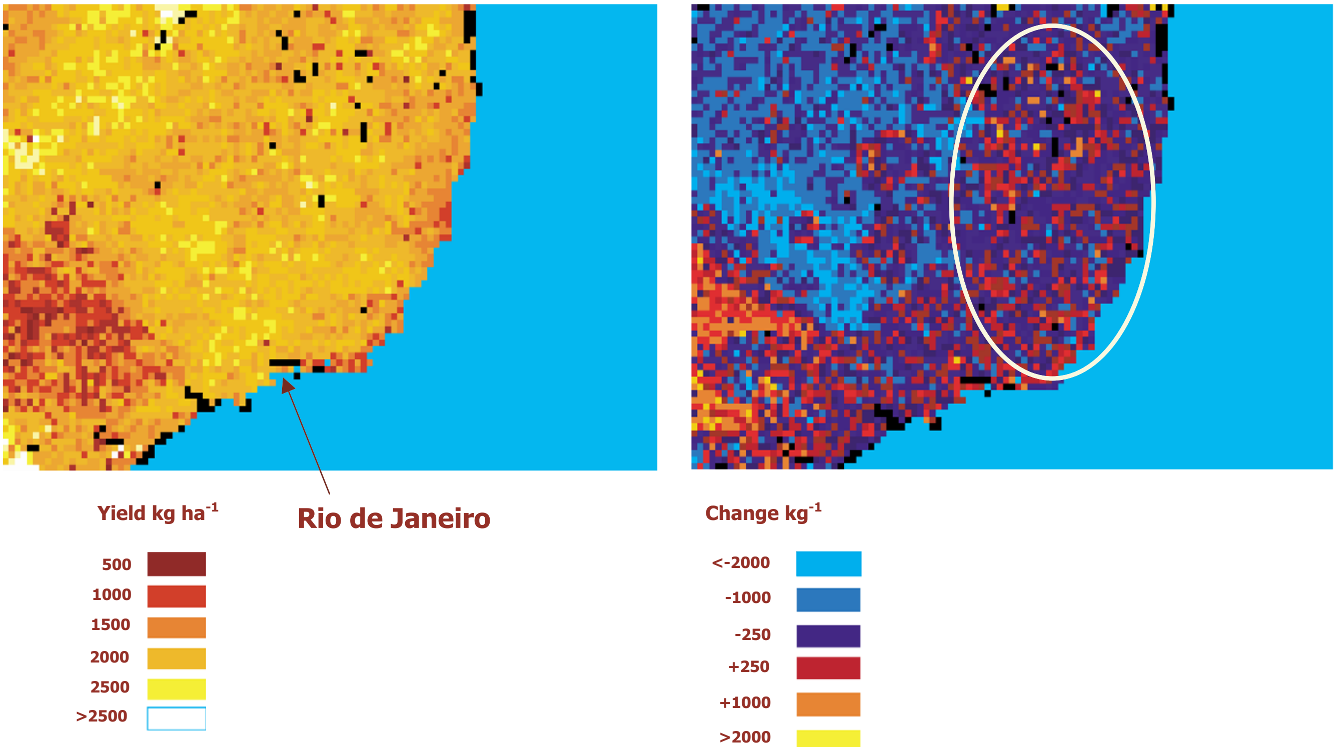


Fig. 2. Eastern Brazil: an area with moderate predicted maize yield changes in 2055, of a size that could readily be handled through agronomy and/or breeding.

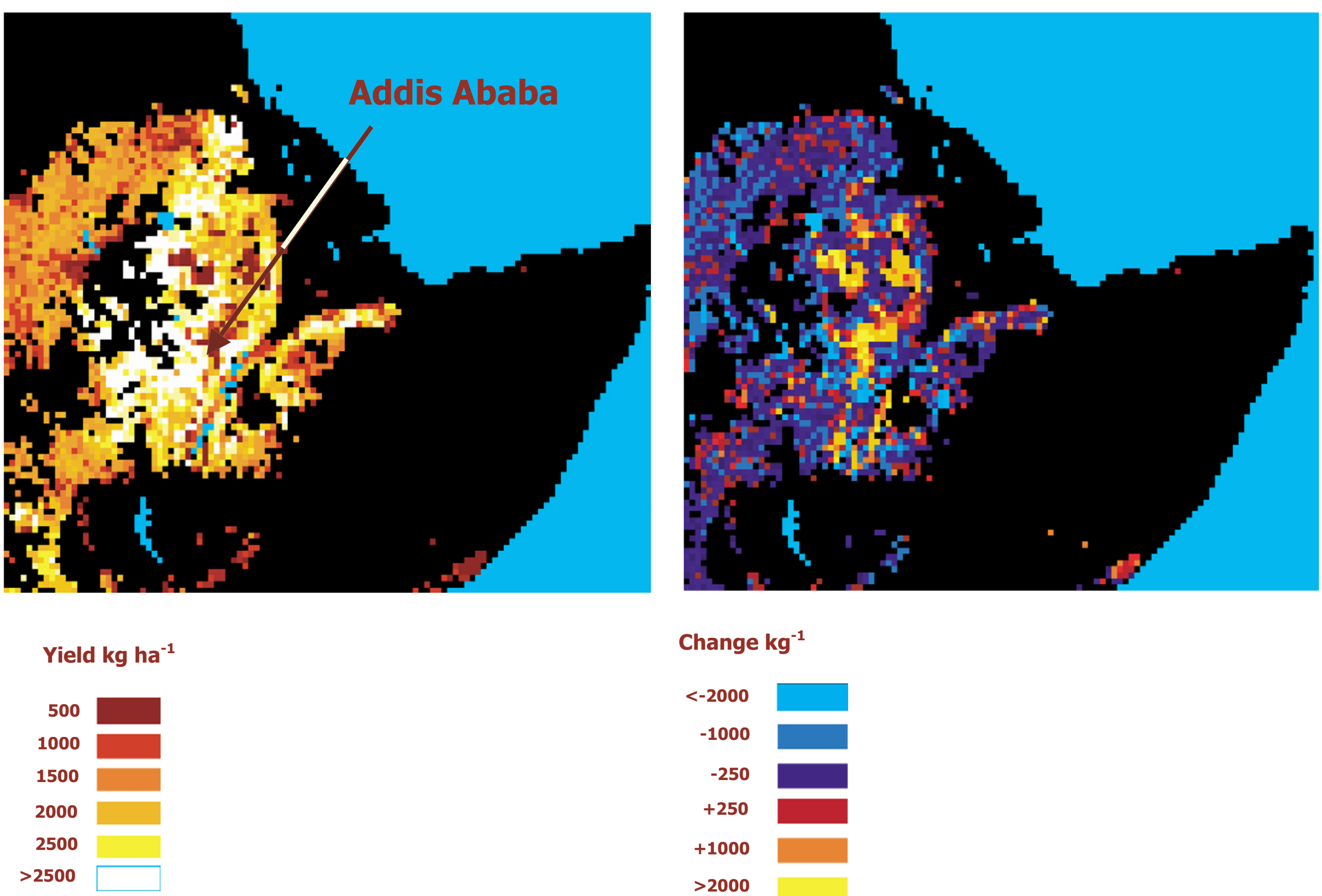


Fig. 3. The Ethiopian highlands, showing areas with large, localized increases in predicted maize yields to 2055, adjacent to areas where yields decrease substantially.

sometimes substantially. We postulate three major types of response of the maize crop to climate change from Fig. 1:

1. Crop yields decrease, but to an extent that can be readily handled by breeding and agronomy. Fig. 2 shows one such area, in eastern Brazil, where the maize yield changes are predicted to be moderate, pixels typically exhibiting a 25% yield difference between the baseline and the 2055 scenarios, interspersed with pixels showing a slight yield advantage.
2. The crop benefits from climate change. One such area is in the Ethiopian highlands surrounding Addis Ababa (Fig. 3), where substantial localized yield increases are predicted, sometimes up to 100%, although many of the pixels showing yield increases are adjacent to pixels where yields are predicted to decline, sometimes drastically.
3. Maize yields decline so drastically, all other things being equal, that major changes may have to be made to the agricultural system, or even human populations may be displaced. An example is shown in Fig. 4, where maize yields in the Venezuelan piedmont are predicted to decline almost to zero. This area is not currently a major maize production area but has been under suitable market conditions in the past. Clearly Venezuela will not be able to count on production from this region in the future.

The overall integration of climate change impacts on production, as expressed in terms of just one of the many agricultural activities in which smallholders may engage, is clearly extremely complex. Table 1 shows averaged country yields for the two scenarios, along with production differences to 2055, and probabilities of maize yields less than 200 kg per ha as an estimate of the probability of crop failure. As noted above, we would fully expect that research and plant breeding will mitigate many of the detrimental effects but these results are what we would expect if farmers continued to plant the same varieties in the same way in the same areas. In nearly three-quarters of the countries, yields decrease to 2055, as a result of temperature increases and rainfall differences becoming less conducive to maize production overall. In some countries, such as Ethiopia and Colombia, overall yields are essentially unchanging to 2055, while a few countries show modest yield increases.

We estimated resultant changes in maize production by country by multiplying simulated yields by country

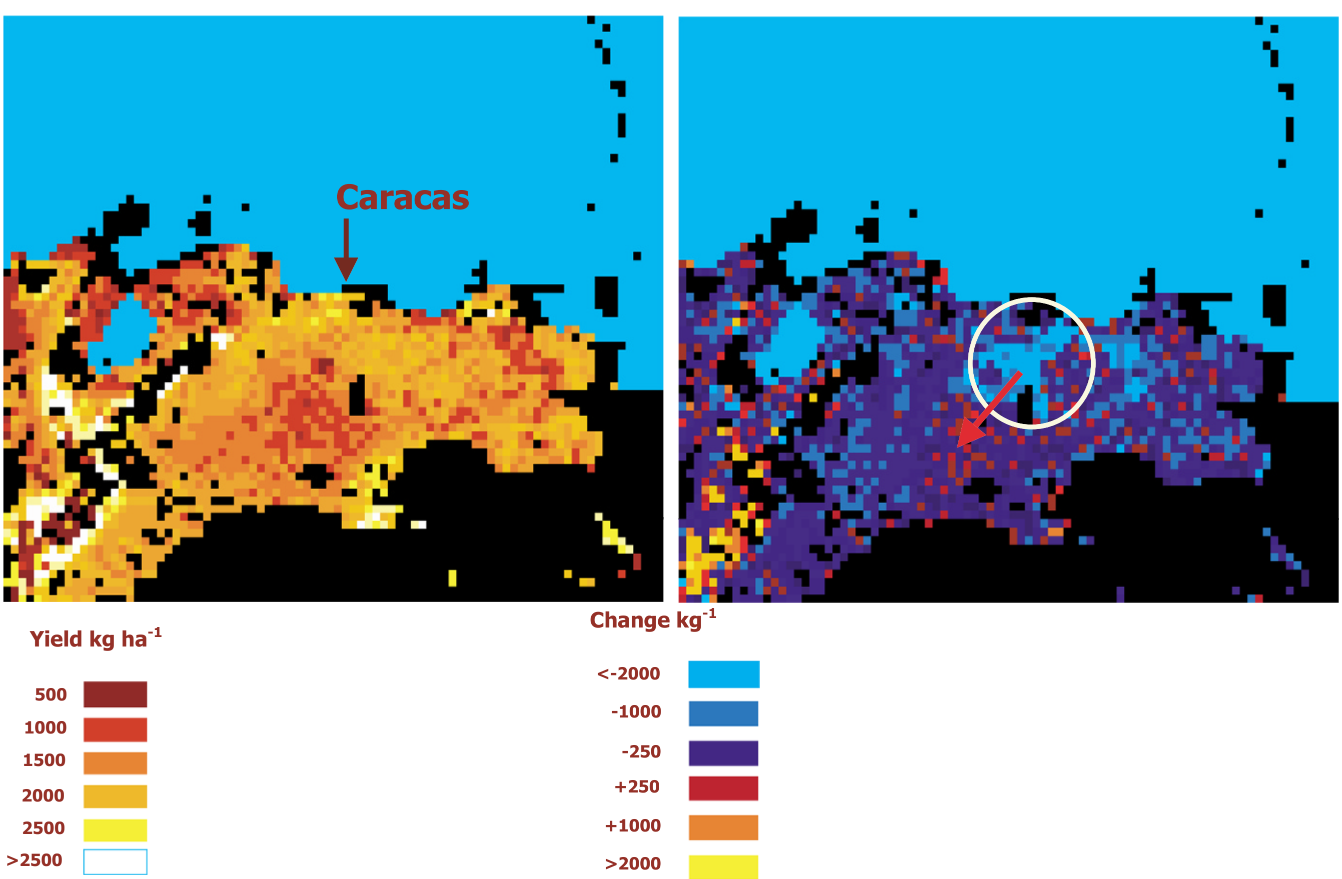


Fig. 4. Venezuela: a case where maize yields to 2055 are predicted to be almost eliminated, indicating that maize production may have to be shifted into wetter areas (for example, to the south-west).

Table 1
Calculated (FAO, 2001) and simulated country yields and production differences to 2055 in smallholder rainfed production systems in countries of Africa and Central and South America

| Country | FAO area, 2000 (ha) | FAO yield, 2000 (kg/ha) | Simulated yield (kg/ha), baseline | Simulated yield (kg/ha), 2055 | Production change, base line to 2055, $t$ | Probability of yield $<200$ kg/ha, baseline | Probability of yield $<200$ kg/ha, 2055 |
|---|---|---|---|---|---|---|---|
| Angola | 672,941 | 636 | 1283 | 1049 | −157,468 | 0.15 | 0.19 |
| Benin | 600,000 | 1105 | 1184 | 977 | −124,200 | 0.09 | 0.11 |
| Botswana | 83,258 | 112 | 990 | 794 | −16,319 | 0.12 | 0.16 |
| Burkina Faso | 280,000 | 1513 | 966 | 809 | −43,960 | 0.04 | 0.06 |
| Burundi | 115,000 | 1082 | 2083 | 1761 | −37,030 | 0.07 | 0.01 |
| Cameroon | 350,000 | 2429 | 1167 | 932 | −82,250 | 0.08 | 0.14 |
| Central Afr Rep | 90,000 | 1189 | 1319 | 1135 | −16,560 | 0.13 | 0.14 |
| Chad | 98,529 | 880 | 1127 | 914 | −20,987 | 0.06 | 0.07 |
| DR Congo | 1,481,852 | 799 | 1548 | 1185 | −537,912 | 0.04 | 0.06 |
| Congo | 3000 | 667 | 1500 | 1294 | −618 | 0.11 | 0.28 |
| Côte d'Ivoire | 700,000 | 816 | 1091 | 1109 | 12,600 | 0.04 | 0.06 |
| Egypt | 843,029 | 7680 | 0 | 0 | 0 | — | — |
| Equatorial Guinea | 0 | 0 | 1500 | 1059 | 0 | 0.67 | 0.40 |
| Eritrea | 28,000 | 429 | 1308 | 1067 | −6748 | 0.08 | 0.09 |
| Ethiopia | 1,450,000 | 1793 | 1842 | 1779 | −91,350 | 0.07 | 0.03 |
| Gabon | 16,000 | 1625 | 1300 | 1147 | −2448 | 0.12 | 0.22 |
| Gambia | 15,000 | 1487 | 1160 | 940 | −3300 | 0.01 | 0.03 |
| Ghana | 700,000 | 1449 | 979 | 835 | −100,800 | 0.07 | 0.13 |
| Guinea | 86,900 | 1036 | 1375 | 1228 | −12,774 | 0.05 | 0.21 |
| Guinea-Bissau | 27,000 | 963 | 1306 | 1126 | −4860 | 0.07 | 0.07 |
| Kenya | 1,500,000 | 1800 | 1154 | 1094 | −90,000 | 0.21 | 0.18 |
| Lesotho | 112,000 | 911 | 934 | 1179 | 27,440 | 0.28 | 0.19 |
| Liberia | 0 | 0 | 1272 | 1253 | 0 | 0.02 | 0.05 |
| Madagascar | 183,580 | 817 | 1299 | 1092 | −38,001 | 0.06 | 0.09 |
| Malawi | 1,350,000 | 1704 | 1541 | 1366 | −236,250 | 0.02 | 0.02 |
| Mali | 140,000 | 1591 | 1053 | 740 | −43,820 | 0.06 | 0.08 |
| Mauritania | 13,000 | 846 | 591 | 583 | −104 | 0.07 | 0.00 |
| Morocco | 237,500 | 400 | 317 | 550 | 55,338 | 0.63 | 0.39 |
| Mozambique | 1,084,153 | 940 | 1227 | 997 | −249,355 | 0.14 | 0.11 |
| Namibia | 38,600 | 1277 | 811 | 654 | −6060 | 0.53 | 0.56 |
| Niger | 6000 | 1333 | 649 | 539 | −660 | 0.08 | 0.12 |
| Nigeria | 3,999,000 | 1400 | 1046 | 858 | −751,812 | 0.06 | 0.11 |
| Rwanda | 75,000 | 840 | 2188 | 2039 | −11,175 | 0.22 | 0.10 |
| Senegal | 100,000 | 910 | 1013 | 849 | −16,400 | 0.06 | 0.08 |
| Sierra Leone | 9588 | 929 | 1444 | 1243 | −1927 | 0.01 | 0.05 |
| Somalia | 250,000 | 840 | 566 | 577 | 2750 | 0.32 | 0.22 |
| South Africa | 3,500,000 | 2029 | 1310 | 1061 | −871,500 | 0.11 | 0.18 |
| Sudan | 76,000 | 697 | 1125 | 932 | −14,668 | 0.06 | 0.08 |
| Swaziland | 54,757 | 1544 | 1318 | 887 | −23,600 | 0.04 | 0.19 |
| Tanzania | 3,010,591 | 847 | 1458 | 1246 | −638,245 | 0.06 | 0.04 |
| Togo | 450,000 | 1097 | 1118 | 889 | −103,050 | 0.05 | 0.10 |
| Uganda | 629,000 | 1742 | 1855 | 1592 | −165,427 | 0.04 | 0.04 |
| Zambia | 750,000 | 1680 | 1535 | 1303 | −174,000 | 0.02 | 0.05 |
| Zimbabwe | 1,300,000 | 1248 | 1546 | 1289 | −334,100 | 0.04 | 0.07 |
| | | | | | | | |
| Argentina | 2,800,000 | 5500 | 1189 | 1065 | −347,200 | 0.35 | 0.38 |
| Belize | 18,000 | 2111 | 1380 | 1032 | −6264 | 0.03 | 0.15 |
| Bolivia | 306,118 | 2214 | 1278 | 1088 | −58,162 | 0.09 | 0.13 |
| Brazil | 12,819,010 | 3237 | 1377 | 1032 | −4,422,558 | 0.08 | 0.08 |
| Chile | 82,550 | 9431 | 260 | 347 | 7182 | 0.72 | 0.58 |
| Colombia | 580,000 | 1828 | 1492 | 1404 | −51,040 | 0.10 | 0.10 |
| Costa Rica | 13,000 | 1731 | 1781 | 1581 | −2600 | 0.04 | 0.02 |
| Ecuador | 459,608 | 1398 | 1538 | 1539 | 460 | 0.12 | 0.10 |
| El Salvador | 262,692 | 2165 | 1781 | 1556 | −59,106 | 0.01 | 0.01 |
| Guatemala | 635,000 | 1575 | 1853 | 1778 | −47,625 | 0.05 | 0.03 |
| Guyana | 2600 | 1192 | 2349 | 1735 | −1596 | 0.00 | 0.00 |
| Honduras | 365,000 | 1370 | 1611 | 1350 | −95,265 | 0.03 | 0.05 |
| Mexico | 7,680,000 | 2500 | 1555 | 1440 | −883,200 | 0.07 | 0.06 |

Table 1 (*continued*)

| Country | FAO area, 2000 (ha) | FAO yield, 2000 (kg/ha) | Simulated yield (kg/ha), baseline | Simulated yield (kg/ha), 2055 | Production change, base line to 2055, *t* | Probability of yield <200 kg/ha, baseline | Probability of yield <200 kg/ha, 2055 |
|---|---|---|---|---|---|---|---|
| Nicaragua | 275,000 | 989 | 1670 | 1375 | −81,125 | 0.02 | 0.04 |
| Panama | 60,000 | 1250 | 1306 | 1068 | −14,280 | 0.09 | 0.16 |
| Paraguay | 370,000 | 2432 | 1187 | 1156 | −11,470 | 0.12 | 0.14 |
| Peru | 523,900 | 2707 | 1574 | 1527 | −24,623 | 0.15 | 0.11 |
| Puerto Rico | 540 | 1870 | 1293 | 1029 | −143 | 0.07 | 0.03 |
| Suriname | 20 | 2000 | 827 | 740 | −2 | 0.25 | 0.25 |
| Uruguay | 42,500 | 1522 | 1413 | 1386 | −1148 | 0.19 | 0.10 |
| Venezuela | 450,000 | 2667 | 1323 | 967 | −569,563 | 0.03 | 0.13 |
| Total | | | | | −11,600,940 | | |

The baseline simulated mean yields differ from the Food and Agriculture Organisation (FAO) country yields because the latter include all maize production—irrigated and/or commercial sector production in addition to smallholder rainfed production. The simulated yields tend to agree better with the FAO yields in countries where irrigated and commercial maize production is limited in extent.

maize areas (FAO, 2001). This will almost certainly not be appropriate for countries where a large fraction of maize production is from high-yielding modern varieties in commercial agriculture; thus figures for Chile, Argentina, Brazil and Mexico, for example, should be treated with considerable caution. An overall reduction of 4.6 million tons of maize per year is simulated to 2025 (results not shown) and a reduction of more than double this to 11.6 million tons per year to 2055, equivalent to about $2 billion per year at current maize prices. Such a reduction in tonnage is equivalent to 10% of the total maize production of Africa and Latin America in 2000 (FAO, 2001). Table 1 also shows that the overall probability of crop failure appears to be related closely to mean yield, although in the case of Peru, it decreases from 1 year in 7 to 1 in 9 even though yields appear to be stable. However, the variation in probability of maize crop failure between regions within countries is as strongly marked as are yields and will deserve careful study in a systems context in any comprehensive assessment.

Another way to present these results and highlight broad agro-ecological differences in the response of the maize crop to climate change is shown in Table 2. Here, mean simulated yields for the two scenarios are broken down by maize mega-environment (Hartkamp et al., 2001), defined on the basis of day length, mean temperature, and precipitation for a 4-month growing season. Yields in the mesic subtropical cold winter environment, for example, increase to 2055 in both Africa and Latin America, presumably because of temperature increases. As might be expected, yields in the dry tropical environments generally decrease.

## 4. Discussion and conclusions

The four generic varieties are used to simulate small farmer rainfed maize production. They do not accurately simulate the high input, often irrigated, production based on modern varieties. Hence we do not match FAO statistics for countries such as Chile and Argentina where these practices are common.

This analysis has highlighted two points. First, the aggregate production impacts of possible future climate change to 2055 on smallholder rainfed maize production in Latin America and Africa are comparatively modest. A 10% decrease in maize yield to 2055 is certainly serious but, as noted above, it can reasonably be expected that this level of decrease will be compensated for by plant breeding and technological interventions in the intervening period, given the history of cereal yield increases since 1950 (Pardey and Beintema, 2001).

Second, the aggregate results hide enormous variability. In some areas, increased yields may allow intensification of agriculture and concomitant increase in rural wealth. However, in areas where a yield reduction of 1 ton or more is expected, considerable disruption to rural life may occur. Where a market economy is well established, alternative income sources may exist and shipping basic foods from other areas may be appropriate. In areas where subsistence agriculture is the norm, there will be grave cause for concern. Alternative production systems will need to be found. The problem is compounded by the fact that for many smallholders, maize stover is a key source of livestock feed during the dry season.

In addition to the fact that maize is commonly used as fodder as well as food, maize is generally grown as just one component of what may be highly complex production systems. In this pilot study, we used the CERES maize model because it is well tried and tested, and recognized as reliable. Maize is a $C_4$ crop and is remarkably tolerant of high temperatures. It is unlikely that some other staple crops would behave as tolerantly under climate change. For example, beans (*Phaseolus vulgaris* L.) have a temperature optimum of around 21°C (Laing et al., 1984) and large areas of Africa and Latin America reliant on this protein source may be badly affected.

Table 2
Average simulated maize yields by maize mega-environment (Hartkamp et al., 2001) for three climate scenarios

| Maize mega-environment | Average simulated maize yield (kg/ha) | | | |
|---|---|---|---|---|
| | Central and South America | | Africa | |
| | Baseline | 2055 | Baseline | 2055 |
| Dry lowland tropical | 1046 | 765 | 487 | 368 |
| Mesic lowland tropical | 716 | 678 | 800 | 715 |
| Wet lowland tropical | 1166 | 974 | 1055 | 928 |
| Pluvial lowland tropical | 1358 | 1293 | 0 | 0 |
| Dry mid-altitude tropical | 1164 | 1092 | 1029 | 907 |
| Mesic mid-altitude tropical | 1361 | 1069 | 1586 | 1370 |
| Wet mid-altitude tropical | 1522 | 1369 | 1400 | 1168 |
| Dry highland tropical | 880 | 796 | 1195 | 1165 |
| Mesic highland tropical | 1469 | 1347 | 1472 | 1882 |
| Wet highland tropical | 1771 | 1985 | 2083 | 2160 |
| Dry lowland subtropical | 0 | 0 | 763 | 656 |
| Mesic lowland subtropical | 1083 | 1019 | 989 | 814 |
| Wet lowland subtropical | 1230 | 1020 | 1251 | 1036 |
| Pluvial lowland subtropical | 1412 | 1252 | 1142 | 1117 |
| Dry mid-altitude subtropical | 568 | 470 | 346 | 572 |
| Mesic mid-altitude subtropical | 1256 | 1331 | 1208 | 984 |
| Wet mid-altitude subtropical | 1657 | 1347 | 1518 | 1256 |
| Dry highland subtropical | 892 | 877 | 449 | 417 |
| Mesic highland subtropical | 1306 | 1488 | 1649 | 1708 |
| Wet highland subtropical | 1886 | 2192 | 2074 | 2208 |
| Mesic subtropical cold winter | 331 | 930 | 187 | 646 |
| Mesic temperate lowland | 937 | 1012 | 801 | 586 |
| Wet temperate lowland | 1120 | 988 | 1019 | 849 |
| Mesic temperate warm | 1043 | 1040 | 1354 | 1008 |
| Wet temperate warm | 1764 | 1571 | 1634 | 1401 |
| Mesic temperate cold | 1265 | 1406 | 1458 | 1183 |
| Wet temperate cold | 1803 | 2300 | 1455 | 1498 |

Maize mega-environments are defined as: day length $h$ (hours): tropical $h<12.5$, subtropical $12.5\leqslant h>13.4$, subtropical winter $h\leqslant 11$, temperate $h\geqslant 13.4$. Mean temperature $t$ (°C): cold $t\leqslant 18$, warm $18<t>24$, hot $t\geqslant 24$. Precipitation $r$ (mm): dry $r<200$, mesic $200\leqslant r>600$, wet $600\leqslant r>2000$, pluvial$\geqslant 2000$.

This analysis goes only a little way towards the kind of comprehensive systems analysis that is required to identify particularly vulnerable smallholders, on whom adaptation strategies might effectively be concentrated to alleviate poverty. These methods need to be applied to assessments that take into account all the food/feed issues and the other enterprises that smallholders engage in, so that the major household impacts can be identified. For example, if production levels of maize grain and stover decrease, from where might the household's dietary energy deficit be met, and which source of fodder could be used to overcome the resultant animal feed deficit? At the same time, it needs to be established whether these comparatively high-resolution methods lead to some sort of consensus on possible impacts obtained from the existing suite of GCMs and GCM experiment ensembles. And do regional (higher-resolution) climate models offer good prospects for robust analyses that are congruent with the results from other GCMs?

With answers to these questions, it should be possible to better identify highly vulnerable farming systems in the tropics and point the way to case studies of adaptation strategies for selected areas of the tropics and subtropics, together with estimates of impacts on poverty and household well-being. Such case studies could include recommendations on how greater system resilience might be brought about, and which policy measures should be developed, in an effort to minimize the social costs and maximize the social benefits that may ensue as a consequence of climate change. The impacts that will be felt at household level depend on many factors related to the production system and the constituent enterprises, as well as the socio-economic and politico-cultural milieu within which rural smallholders live. Being able to assess impacts at high resolution is critical and linking the results of such studies to poverty maps and natural resource vulnerability assessments should lead to substantial improvements in targeting policies and technology options that really can help the poor. Such options might include, for example, more conducive policies for market development for new and existing crop and livestock products, breeding drought-tolerant crops, modified farm management practices and improved infrastructure for off-farm employment generation. Given the length of time needed for effective agricultural research cycles, we need to identify much more clearly what the system-level impacts of climate change on poor households might be, and, if these are far-reaching, then we need to start work on adaptive and ameliorative options immediately, as a matter of urgency.

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## References

Batjes, N.H., Bridges, E.M., 1994. Potential emissions of radiatively active trace gases from soil to atmosphere with special reference to

methane: development of a global database (wise). Journal of Geophysical Research 99(D8), 16479–16489.
Bowen, W.T., Jones, J.W., Carsky, R.J., Quintana, J.O., 1992. Evaluation of the nitrogen submodel of CERES-maize following legume green manure incorporation. Agronomy Journal 85, 153–159.
Cullen, M.J.P., 1993. The unified forecast/climate model. Meteorological Magazine 122, 81–95.
Donatelli, M., Campbell, G.S., 1997. A simple model to estimate global solar radiation. PANDA Project, Subproject 1, Series 1, Paper 26, ISCI, Bologna, Italy, 3pp.
Fischer, G., Shah, M., van Velthuizen, H., Nachtergaele, F.O., 2001. Global Agro-Ecological Assessment for Agriculture in the Twenty-first Century. International Institute for Applied Systems Analysis, Laxenburg, Austria.
Food and Agriculture Organization of the United Nations (FAO), 1978. Report on the AgroEcological Zones Project, Vol. 1. Methodology and Results for Africa. UNESCO, Paris; FAO, Rome.
Food and Agriculture Organization of the United Nations (FAO), 1995. Digital Soil Map of the World and Derived Soil Properties, Version 3.5. Land and Water Digital Media Series 1, FAO, Rome.
Food and Agriculture Organization of the United Nations (FAO), 2001. FAOSTAT: FAO Statistical Databases. Online at http://apps.fao.org, November 2001.
Hansen, J.W., Knapp, E.B., Jones, J.W., 1997. Determinants of sustainability of a Colombian hillside farm. Experimental Agriculture 33, 425–448.
Hartkamp, A.D., White, J.W., Rodríguez Aguilar, A., Bänziger, M., Srinivasan, G., Granados, G., Crossa, J., 2001. Maize Production Environments Revisited. A GIS-Based Approach. International Maize and Wheat Improvement Centre, Mexico, DF.
Intergovernmental Panel on Climate Change (IPCC), 2001a. Climate Change 2001: The Scientific Basis. Working Group 1 Contribution to the IPCC Third Assessment Report. Online at http://www.ipcc.ch, November 2001.
Intergovernmental Panel on Climate Change (IPCC), 2001b. The Regional Impacts of Climate Change: An Assessment of Vulnerability. Online at http://www.ipcc.ch, November 2001.
Jones, P.G., Thornton, P.K., 1993. A rainfall generator for agricultural applications in the tropics. Agricultural and Forest Meteorology 63, 1–19.
Jones, P.G., Thornton, P.K., 1997. Spatial and temporal variability of rainfall related to a third-order Markov model. Agricultural and Forest Meteorology 86, 127–138.
Jones, P.G., Thornton, P.K., 1999. Fitting a third-order Markov rainfall model to interpolated climate surfaces. Agricultural and Forest Meteorology 97, 213–231.
Jones, P.G., Thornton, P.K., 2000. MarkSim: software to generate daily weather data for Latin America and Africa. Agronomy Journal 92, 445–453.
Jones, P.G., Thornton, P.K., 2001. Spatial modelling of risk in natural resource management: applying plot-level, plant-growth modelling to regional analysis. Conservation Ecology 5(2), 27. URL: http://www.consecol.org/vol5/iss2/art27, January 2002.
Laing, D.R., Jones, P.G., Davis, J.H.C., 1984. In: Goldsworthy, P.R., Fisher, N.M. (Eds.), The Physiology of Tropical Field Crops. Wiley, New York, pp. 305–351.
Loveland, T.R., Reed, B.C., Brown, J.F., Ohlen, D.O., Zhu, Z., Yang, L., Merchant, J., 2000. Development of global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. International Journal of Remote Sensing 21(6), 1303–1330. Global Land Cover Characteristics Database Version 1.2, available online at http://edcdaac.usgs.gov/glcc/glcc.html, November 2001.
Magrin, G.O., Travasso, M.I., Díaz, R., Rodríguez, R., 1997. Vulnerability of the agricultural systems of Argentina to climate change. Climate Research 9, 31–36.
Muchena, P., Iglesias, A., 1995. In: Rosenzweig, C., et al. (Ed.), Climate Change and Agriculture: Analysis of Potential International Impacts. American Society of Agronomy Special Publication 59, Madison, WI, pp. 229–239.
Openshaw, S., Turner, A., 1998. Predicting the impact of global climatic change on land use in Europe. Medalus III Project 9.1, GIS-based socio-economic modelling. Online at http://www.medalus.leeds.ac.uk/SEM/home.htm, November 2001.
Pardey, P.G., Beintema, N.M., 2001. Slow magic: agricultural R&D a century after Mendel. Food Policy Report, International Food Policy Research Institute, Washington, DC.
Ritchie, J.T., 1998. Soil water balance and plant water stress. In: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, The Netherlands, pp. 41–54.
Ritchie, J.T., Singh, U., Godwin, D.C., Bowen, W.T., 1998. In: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Kluwer, Dordrecht, pp. 79–98.
Rosenzweig, C., Hillel, D., 1998. Climate Change and the Global Harvest. Potential Impacts of the Greenhouse Effect on Agriculture. Oxford University Press, Oxford, New York.
Rosenzweig, C., Iglesias, A., 2001. Potential impacts of climate change on world food supply. Data sets from a major crop modeling study. Online at http://beta.sedac.ciesin.columbia.edu/giss_crop_study/index.html, November 2001.
Schulze, R., 2000. Transcending scales of space and time in impact studies of climate and climate change on agrohydrological responses. Agriculture, Ecosystems and Environment 82, 185–212.
Thornton, P.K., Saka, A.R., Singh, U., Kumwenda, J.D.T., Brink, J.E., Dent, J.B., 1995. Application of a maize crop simulation model in the central region of Malawi. Experimental Agriculture 31, 213–226.
Thornton, P.K., Kruska, R.L., Henninger, N., Kristjanson, P.M., Reid, R.S., Atieno, F., Odero, A., Ndegwa, T., 2002. Poverty and livestock mapping. Final Report to the UK Department for International Development. ILRI, Nairobi, Kenya.
Wafula, B., 1995. Applications of crop simulation in agricultural extension and research in Kenya. Agricultural Systems 49, 399–412.
Watson, R.T., 2001. In: CGIAR Annual Report 2000, The Challenge of Climate Change: Poor Farmers at Risk. Consultative Group on International Agricultural Research Secretariat, The World Bank, Washington, DC, pp. 8–12.
Wood, S., Sebastian, K., Scherr, S.J., 2000. Pilot Analysis of Global Ecosystems: Agroecosystems. International Food Policy Research Institute and World Resources Institute, Washington, DC.
World Bank, 2001. World Development Report 2000/2001: Attacking Poverty. Oxford University Press, New York.