For hydrocarbon (simplified in this model to just CH_4) concentrations of 1.4 mmol/kg, the maximum W/R is 64, assuming 100% conversion of CO_2 to CH_4 and an initial (but high) CO_2 concentration of ~4000 ppm in the basement rocks (*37*) (fig. S2). This W/R is at the low end of those predicted from the Sr and Nd isotopic compositions of LCHF serpentinites (*37*); however, the samples from seafloor outcrops almost certainly have a reaction history different from that of the rocks directly supplying the present-day fluids at Lost City. More typical and lower initial basement rock CO_2 concentrations would yield lower W/Rs. On the basis of a system constrained by a 400-ppm CO_2 concentration in the basement rocks (*27*) and a conversion of ~50% (as suggested by the He and CO_2 data), we posit that the fluids feeding the LCHF have reacted with rocks in a W/R of less than 5 (fig. S2).

Lost City may be just one of many, as yet undiscovered, off-axis hydrothermal systems. Hydrocarbon production by FTT could be a common means for producing precursors of life-essential building blocks in ocean-floor environments or wherever warm ultramafic rocks are in contact with water.

References and Notes

1. J. L. Charlou, J. P. Donval, Y. Fouquet, B. P. Jean, N. Holm, *Chem. Geol.* **191**, 345 (2002).
2. T. A. Abrajano *et al.*, *Chem. Geol.* **71**, 211 (1988).
3. R. B. Anderson, *The Fischer-Tropsch Synthesis* (Academic Press, Orlando, FL, 1984).
4. D. I. Foustoukos, W. E. Seyfried Jr., *Science* **304**, 1002 (2004).
5. T. M. McCollom, J. S. Seewald, *Earth Planet. Sci. Lett.* **243**, 74 (2006).
6. D. S. Kelley *et al.*, *Nature* **412**, 145 (2001).
7. D. S. Kelley *et al.*, *Science* **307**, 1428 (2005).
8. G. L. Früh-Green *et al.*, *Science* **301**, 495 (2003).
9. J. A. Karson *et al.*, *Geochem. Geophys. Geosyst.* **7**, Q06016 (2006).
10. D. E. Allen, J. Seyfried, W. E. *Geochim. Cosmochim. Acta* **68**, 1347 (2004).
11. R. P. Lowell, P. A. Rona, *Geophys. Res. Lett.* **29**, 1531 (2002).
12. G. Proskurowski, M. D. Lilley, D. S. Kelley, E. J. Olson, *Chem. Geol.* **229**, 331 (2006).
13. M. D. Lilley, D. A. Butterfield, J. E. Lupton, E. J. Olson, *Nature* **422**, 878 (2003).
14. W. E. Seyfried Jr., D. I. Foustoukos, Q. Fu, *Geochim. Cosmochim. Acta* **71**, 3872 (2007).
15. B. Martin, W. S. Fyfe, *Chem. Geol.* **6**, 185 (1970).
16. M. D. Lilley *et al.*, *Nature* **364**, 45 (1993).
17. J. A. Welhan, J. E. Lupton, *AAPG Bull.* **71**, 215 (1987).
18. M. J. Whiticar, *Chem. Geol.* **161**, 291 (1999).
19. B. Sherwood Lollar *et al.*, *Chem. Geol.* **226**, 328 (2006).
20. J. M. Hunt, *Petroleum Geochemistry and Geology* (Freeman, New York, 1996).
21. Y. A. Taran, G. A. Kliger, V. S. Sevastianov, *Geochim. Cosmochim. Acta* **71**, 4474 (2007).
22. B. Sherwood Lollar, T. D. Westgate, J. A. Ward, G. F. Slater, C. G. Lacrampe, *Nature* **416**, 522 (2002).
23. A. Schimmelmann, A. L. Sessions, M. Mastalerz, *Annu. Rev. Earth Planet. Sci.* **34**, 501 (2006).
24. W. F. Giggenbach, *Geochim. Cosmochim. Acta* **61**, 3763 (1997).
25. J. Horita, M. E. Berndt, *Science* **285**, 1055 (1999).
26. P. A. Rona, L. Widenfalk, K. Bostroem, *J. Geophys. Res.* **92**, 1417 (1987).
27. G. L. Früh-Green, J. A. D. Connolly, A. Plas, D. S. Kelley, B. Grobety, in *The Subseafloor Biosphere at Mid-Ocean Ridges*, W. S. D. Wilcock, E. F. Delong, D. S. Kelley, J. A. Baross, C. S. Cary, Eds. (American Geophysical Union, Washington, DC, 2004), vol. 144, pp. 119–136.
28. Low concentrations of CO_2 with large contributions from modern seawater bicarbonate prevent the determination of presumably near–radiocarbon dead end-member ^{14}C contents of Lost City fluids.
29. G. Proskurowski, M. D. Lilley, T. A. Brown, *Earth Planet. Sci. Lett.* **225**, 53 (2004).
30. J. C. Alt, D. A. H. Teagle, *Geochim. Cosmochim. Acta* **63**, 1527 (1999).
31. B. Marty, I. N. Tolstikhin, *Chem. Geol.* **145**, 233 (1998).
32. Seawater bicarbonate accounts for 55 to 98% of the measured CO_2 concentrations in LCHF fluids. The large extrapolations involved in the calculation of end-member CO_2 concentrations introduce large errors that propagate during the determination of end-member $\delta^{13}C$-CO_2 values by mass-isotope balance. However, measured $\delta^{13}C$-CO_2 values were −5 to −2‰, indicating mixing between seawater bicarbonate (−0.40‰) and an end-member more depleted in ^{13}C. The best-quality sample yielded an end-member $\delta^{13}C$-CO_2 value of −8.7 ± 1.5‰, and samples with greater uncertainties had lower values.
33. D. S. Kelley, G. L. Früh-Green, *Geochim. Cosmochim. Acta* **65**, 3325 (2001).
34. W. J. Brazelton, M. O. Schrenk, D. S. Kelley, J. A. Baross, *Appl. Environ. Microbiol.* **72**, 6257 (2006).
35. M. O. Schrenk, D. S. Kelley, S. A. Bolton, J. A. Baross, *Environ. Microbiol.* **6**, 1086 (2004).
36. D. S. Kelley, G. L. Früh-Green, *J. Geophys. Res.* **104**, 10439 (1999).
37. A. Delacour, P. Schaeffer, S. M. Bernasconi, G. L. Früh-Green, *Eos Trans. AGU* **87**, B31B (2006).
38. We thank the captains and crews of the R/V *Atlantis* and R/V *Ronald H. Brown*, and the crews of the DSV *Alvin* and the ROV *Hercules* for their indispensable expertise in deep-sea oceanography. We also thank R. Ballard and the Institute for Exploration for their efforts during the 2005 Lost City expedition, a proof-of-concept cruise directed by satellite-linked shore-based investigators. This work was supported in part by NSF grant OCE0137206, the NOAA Ocean Exploration Program, and a fellowship from the Woods Hole Oceanographic Institution Deep Ocean Exploration Institute. We thank D. Butterfield for providing Mg data. This manuscript benefited greatly from the comments by two anonymous reviewers.

Supporting Online Material

www.sciencemag.org/cgi/content/full/319/5863/604/DC1
Materials and Methods
Figs. S1 and S2
Tables S1 and S2
References

1 October 2007; accepted 14 December 2007
10.1126/science.1151194

Prioritizing Climate Change Adaptation Needs for Food Security in 2030

David B. Lobell,[1,2]* Marshall B. Burke,[1] Claudia Tebaldi,[3] Michael D. Mastrandrea,[4] Walter P. Falcon,[1] Rosamond L. Naylor[1]

Investments aimed at improving agricultural adaptation to climate change inevitably favor some crops and regions over others. An analysis of climate risks for crops in 12 food-insecure regions was conducted to identify adaptation priorities, based on statistical crop models and climate projections for 2030 from 20 general circulation models. Results indicate South Asia and Southern Africa as two regions that, without sufficient adaptation measures, will likely suffer negative impacts on several crops that are important to large food-insecure human populations. We also find that uncertainties vary widely by crop, and therefore priorities will depend on the risk attitudes of investment institutions.

Adaptation is a key factor that will shape the future severity of climate change impacts on food production (*1*). Although relatively inexpensive changes, such as shifting planting dates or switching to an existing crop variety, may moderate negative impacts, the biggest benefits will likely result from more costly measures including the development of new crop varieties and expansion of irrigation (*2*). These adaptations will require substantial investments by farmers, governments, scientists, and development organizations, all of whom face many other demands on their resources. Prioritization of investment needs, such as through the identification of "climate risk hot spots" (*3*), is therefore a critical issue but has received limited attention to date.

We consider three components to be essential to any prioritization approach: (i) selection of a time scale over which impacts are most relevant to investment decisions, (ii) a clear definition of criteria used for prioritization, and (iii) an ability to evaluate these criteria across a suite of crops and regions. Here, we focus on food security impacts by 2030: a time period most relevant to large agricultural investments, which typically take 15 to 30 years to realize full returns (*4*, *5*).

We consider several different criteria for this time scale. First is the importance of the

[1]Food Security and Environment Program, Woods Institute for the Environment and the Freeman Spogli Institute for International Studies, Stanford University, Stanford, CA 94305, USA. [2]Lawrence Livermore National Laboratory (LLNL), Livermore, CA 94550, USA. [3]National Center for Atmospheric Research, Boulder, CO 80305, USA. [4]Woods Institute for the Environment, Stanford University, Stanford, CA 94305, USA.

*To whom correspondence should be addressed. E-mail: dlobell@stanford.edu

crop to a region's food-insecure human population [hunger importance (HI)]. Second is the median projected impact of climate change on a crop's production by 2030 (indicated by C50), assuming no adaptation. For this analysis, we generate multiple (i.e., 100) projections of impacts based on different models of climate change and crop response, in order to capture relevant uncertainties. The projections are then ranked, and the average of the 50th and 51st values are used as the median. A third criterion is the fifth percentile of projected impacts by 2030 (where C05 indicates the fifth value of the ranked projections), which we use to represent the lower tail or "worst case" among the projections. Finally, we consider the 95th percentile of projected impacts by 2030 (where C95 indicates the 95th value of the ranked projections), which we use to represent the upper tail or "best case" among the projections.

We first identified 12 major food-insecure regions, each of which (i) comprise groups of countries with broadly similar diets and agricultural production systems and (ii) contain a notable share of the world's malnourished individuals as estimated by the Food and Agriculture Organization (FAO) (Table 1; see fig. S1 for details on regions). For each region, we computed the HI value for each crop by multiplying the number of malnourished individuals by the crop's percent contribution to average per capita calorie consumption [see supporting online material (SOM) Text S1 and table S1]. A hunger importance ranking (HIR) was then generated by ranking the HI values for all crop-by-region combinations. Rice, maize, and wheat contribute roughly half of the calories currently consumed by the world's poor and only 31% of the calories consumed by those in sub-Saharan Africa, illustrating the importance of considering additional crops in food security assessments. The use of projected malnourished populations in 2030 rather than current population values had a very small influence on the rankings (table S2).

Several options exist for evaluating climate change impacts across a suite of crops and regions (SOM Text S2). We used data sets on historical crop harvests (*6*), monthly temperatures and precipitation, and maps of crop locations to develop statistical crop models for 94 crop-region combinations spanning the 12 study regions (see SOM Text S3; results summarized in Table 1). Of these combinations, 46% (43) exhibited a statistically significant model ($P < 0.05$), and 22% (21) had a model R^2 of at least 0.3. As seen in the examples for wheat in South and West Asia (fig. S3), in some cases the model's strength came primarily from a (typically negative) temperature effect on yield, whereas, in other cases, a (typically positive) rainfall effect provided most of the explanatory power.

The crop temperature sensitivities estimated by the statistical models were compared with corresponding values from previous studies that relied on established process-based models within the same regions (SOM Text S4). Our statistical estimates generally overlapped the lower end of the range of previous estimates, indicating that impacts estimated by the statistical models may be considered conservative but in reasonable agreement with estimates from process-based approaches.

To project climate changes for the crop regions, along with their uncertainties, we used output from 20 general circulation models (GCMs) that have contributed to the World Climate Research Programme's Coupled Model Intercomparison Project phase 3 (WCRP CMIP3) (*7*). Median projections of average temperature change from 1980–2000 to 2020–2040 were roughly 1.0°C in most regions, with few models projecting less than 0.5°C warming in any season and some models warming by as much as 2.0°C (Fig. 1A). In contrast to the unanimous warming, models were mixed in the direction of simulated precipitation change. All regions had at least one model with positive and one model with negative projected precipitation changes, with median projections ranging from about –10% to +5% (Fig. 1B). Some relevant tendencies of current GCMs, as noted in (*8*), are toward precipitation decreases during December to February (DJF) in South Asia and Central America, precipitation decreases in June to August (JJA) in Southern Africa, Central America, and Brazil, and precipitation increases in DJF in East Africa.

We estimated a probability distribution of production changes for 2030 (the average from

Table 1. Regions evaluated in this study and selected summary statistics. Countries within each region are indicated in the SOM.

Region	Code	Malnourished: Millions of people	Malnourished: World total (%)	Crops modeled	Crops with significant model*
South Asia	SAS	262.6	30.1%	9	7
China	CHI	158.5	18.2%	7	2
Southeast Asia	SEA	109.7	12.6%	7	4
East Africa	EAF	79.0	9.1%	10	2
Central Africa	CAF	47.6	5.5%	8	0
Southern Africa	SAF	33.3	3.8%	8	6
West Africa	WAF	27.5	3.2%	8	2
Central America and Caribbean	CAC	25.4	2.9%	5	2
Sahel	SAH	24.9	2.9%	7	7
West Asia	WAS	21.9	2.5%	10	4
Andean region	AND	21.4	2.5%	9	3
Brazil	BRA	13.5	1.6%	6	4
Total	ALL	825.3	94.7%	94	43

*A model was judged significant if it explained more than 14% of variance in yield or production ($R^2 > 0.14$). This threshold was based on the 95th percentile of the R^2 statistic from a Monte Carlo experiment, which computed 1000 multiple regression models for a randomly generated 42-year time series with two random predictor variables.

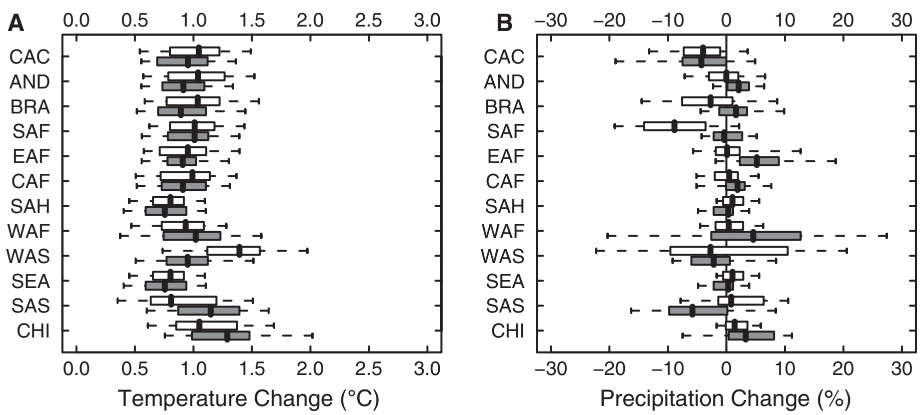

Fig. 1. Summary of projected (**A**) temperature (°C) and (**B**) precipitation (%) changes for 2030 (the averages from 2020 to 2039 relative to those from 1980 to 1999) based on output from 20 GCMs and three emission scenarios. Gray boxes show DJF averages and white boxes show JJA averages. Dashed lines extend from 5th to 95th percentile of projections, boxes extend from 25th to 75th percentile, and the middle vertical line within each box indicates the median projection.

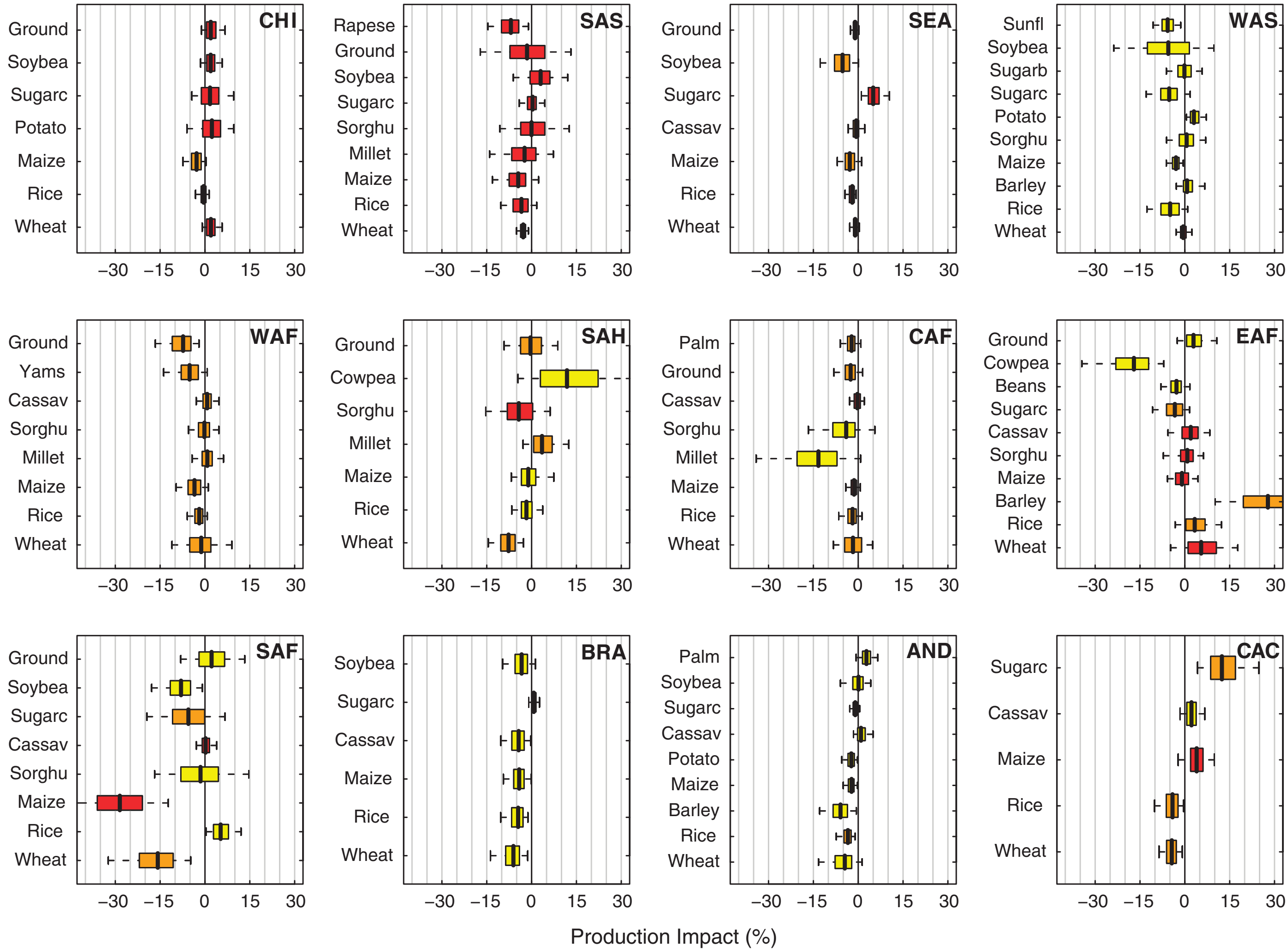

Fig. 2. Probabilistic projections of production impacts in 2030 from climate change (expressed as a percentage of 1998 to 2002 average yields). Red, orange, and yellow indicate a HIR of 1 to 30 (more important), 31 to 60 (important), and 61 to 94 (less important), respectively. Dashed lines extend from 5th to 95th percentile of projections, boxes extend from 25th to 75th percentile, and the middle vertical line within each box indicates the median projection. Region codes are defined in Table 1.

Table 2. Crop priority lists based on different criteria. C05 = 5th percentile of projected impacts (5th lowest out of 100 projections); C50 = 50th percentile (median); C95 = 95th percentile. Results are shown only for the HIR = 1 to 30 and HIR = 31 to 60 categories.

HIR value	Criterion	Crops
1 to 30	C05 < –10%	South Asia millet, groundnut, rapeseed; Sahel sorghum; Southern Africa maize
	C50 < –5%	South Asia rapeseed; Southern Africa maize
	C95 < 0%	South Asia wheat; Southeast Asia rice; Southern Africa maize
31 to 60	C05 < –10%	Southeast Asia soybean; West Asia rice; Western Africa wheat, yams, groundnut; Sahel wheat; East Africa sugarcane; Southern Africa wheat, sugarcane; Brazil wheat, rice; Andean Region wheat; Central America rice
	C50 < –5%	Southeast Asia soybean; West Asia rice; Western Africa yams, groundnut; Sahel wheat; Southern Africa wheat, sugarcane; Brazil wheat
	C95 < 0%	Western Africa groundnut; Sahel wheat; Southern Africa wheat; Brazil wheat, rice; Central America wheat, rice

2020 to 2039 relative to that from 1980 to 1999) for each crop using a Monte Carlo procedure that propagated both climate and crop uncertainties (*9*). To facilitate comparison between crops and regions, we expressed production changes for all crops as a percentage of average values for 1998 to 2002. The impact projections are summarized in Fig. 2.

For simplicity, we consider three general classes of projections. First, several projections (e.g., Southern Africa maize and wheat) are consistently negative, with an estimated 95% or greater chance that climate changes will harm crop production in the absence of adaptation (C95 < 0). These cases generally arise from a strong dependence of historical production variations on temperature, combined with projected warming large enough to overwhelm the uncertain impacts of precipitation changes.

Second, there are many cases with large uncertainties, with model impacts ranging from substantially negative to positive (e.g., South Asia groundnut, Southern Africa sorghum). These cases usually arise from a relatively strong dependence of historical production on rainfall, combined with large uncertainties in future precipitation changes. More precise projections of precipitation would therefore be particularly useful to reduce impact uncertainties in these situations. Large uncertainties also arise in some cases (e.g., cowpea in East Africa) from an estimated production response to historical temperature that is strongly negative but also highly uncertain.

Finally, there are many cases characterized by a narrow 90% confidence interval of impacts within ±5% of zero. In a few cases, such as wheat in West Asia, this reflects a strong effect of historical rainfall variations (fig. S1), combined with a relatively narrow range of rainfall projections during the growing season (Fig. 1; West Asia wheat is grown in DJF). In most cases, such as cassava in West Africa, the narrow confidence intervals result from a relatively weak relationship between historical production and growing-season climate. Therefore, we can only say that the likely impacts appear small, given the current data sets and models used to describe crop responses to climate. In cases with low model R^2, approaches other than the FAO-based regression models used here may be more appropriate.

Based on the above projections, we identified a small subset of crops that met different prioritization criteria (Table 2). First, crops were separated into groups of "more important" (HIR = 1 to 30), "important" (HIR = 31 to 60), and "less important" (HIR = 61 to 94). Within each category, we identified crops below three thresholds: the first corresponding to instances where at least 5% of the models predicted greater than 10% loss of production (C05 < –10%), the second to where at least half the models projected greater than a 5% production loss (C50 < –5%), and the third to where at least 95% of the models predicted some production loss (C95 < 0%).

Although several crops met more than one of these criteria, such as maize in Southern Africa and rapeseed in South Asia, the varying estimates of uncertainty for different crops, in general, resulted in noticeable differences when prioritizing crops on the basis of the three different thresholds (Table 2). For example, a relatively weak relationship was found between values at the two tails of the projection distributions—C05 and C95—across all crops (fig. S4). This result indicates a need to explicitly consider uncertainty and risk attitudes when setting priorities, which is an issue that has received limited attention (*10*).

Because attitudes toward risk differ, and given that impact projections for some crops are more uncertain than those for other crops, various institutions might derive different priorities from the results in Table 2. For example, one set of institutions might wish to focus on those cases where negative impacts are most likely to occur, in order to maximize the likelihood that investments will generate some benefits. By this criterion (C95 < 0%), South Asia wheat, Southeast Asia rice, and Southern Africa maize appear as the most important crops in need of adaptation investments.

Others might argue that adaptation activities that do not account for worst-case projections will be inadequate in the face of low-probability, high-consequence climate impacts: that is to say, investments should target those crops and regions for which some models predict very negative outcomes. A different subset of crops is identified for this criterion (C05 < –10%), with several South Asian crops, Sahel sorghum, and (again) Southern Africa maize appearing as the most in need of attention.

Either of these risk attitudes could be applied with an explicit regional focus. For a sub-Saharan African institution interested in investing where negative impacts are most likely to occur [where median impact projections are substantially negative (C50 < –5%) or where most climate models agree that negative impacts are likely to occur (C95 < 0%)], priority investments would include Southern Africa maize, wheat, and sugarcane, Western Africa yams and groundnut, and Sahel wheat.

Despite the many assumptions and uncertainties associated with the crop and climate models used (SOM Text S5), the above analysis points to many cases where food security is clearly threatened by climate change in the relatively near-term. The importance of adaptation in South Asia and Southern Africa appears particularly robust, because crops in these regions appear for all criteria considered here (Table 2). The results also highlight several regions (e.g., Central Africa) where climate-yield relationships are poorly captured by current data sets, and therefore future work in this regard is needed to inform adaptation efforts.

Impacts will likely vary substantially within individual regions according to differences in biophysical resources, management, and other factors. The broad-scale analysis presented here was intended only to identify major areas of concern, and further studies at finer spatial scales are needed to resolve local hot spots within regions. Consideration of other social and technological aspects of vulnerability, such as the existing adaptive capacity in a region or the difficulty of making adaptations for specific cropping systems, should also be integrated into prioritization efforts. Although we do not attempt to identify the particular adaptation strategies that should be pursued, we note that, in some regions, switching from highly impacted to less impacted crops may be one viable adaptation option. In this case, the identification of less impacted crops is another valuable outcome of a comprehensive approach that simultaneously considers all crops relevant to the food-insecure.

References and Notes

1. W. Easterling *et al.*, in *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge Univ. Press, Cambridge, 2007), pp. 273–313.
2. C. Rosenzweig, M. L. Parry, *Nature* **367**, 133 (1994).
3. I. Burton, M. van Aalst, "Look before you leap: A risk management approach for incorporating climate change adaptation in World Bank operations" (World Bank, Washington, DC, 2004).
4. J. M. Alston, C. Chan-Kang, M. C. Marra, P. G. Pardey, T. J. Wyatt, "A meta-analysis of rates of return to agricultural R&D: Ex pede Herculem?" (International Food Policy Research Institute, Washington, DC, 2000).
5. J. Reilly, D. Schimmelpfennig, *Clim. Change* **45**, 253 (2000).
6. We used FAO data on national crop production and area, which include quantities consumed or used by the producers in addition to those sold on the market.
7. Model simulations under three SRES (Special Report on Emissions Scenarios) emission scenarios corresponding to relatively low (B1), medium (A1b), and high (A2) emission trajectories were used. Although the mean projections for the emission scenarios exhibit very small differences out to 2030, the use of three scenarios provided a larger sample of simulations with which to assess climate uncertainty. For all simulations, average monthly output for 1980–1999 was subtracted from that of 2020–2039 to compute monthly changes in temperature and precipitation.
8. J. H. Christensen *et al.*, in *Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, S. Solomon *et al.*, Eds. (Cambridge Univ. Press, Cambridge, 2007), pp. 847–940.
9. Namely, the crop regression model was fit with a bootstrap sample from the historical data, and the coefficients from the regression model were then multiplied by projected changes in average temperature and precipitation, which were randomly selected from the CMIP3 database. This process was repeated 100 times for each crop. Bootstrap resampling is a common approach to estimate uncertainty in regression coefficients, although this addresses only the component of model uncertainty that arises from a finite historical sample and not the potential uncertainty from structural errors in the model. Similarly, the representation of climate uncertainty by equally weighting all available GCMs is a common approach but could potentially be improved, such as by weighting models according to their agreement with the model consensus and with historical observations. Nonetheless, the resulting probability distributions incorporate reasonable measures of both climate and crop uncertainty, and thus should fairly reflect both the absolute and relative level of uncertainties between crops.
10. B. Smit *et al.*, in *Climate Change 2001: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change* (Cambridge Univ. Press, Cambridge, 2001), pp. 877–912.
11. We thank D. Battisti, C. Field, and three anonymous reviewers for helpful comments. D.B.L. was supported by a Lawrence Fellowship from LLNL. Part of this work was performed under the auspices of the U.S. Department of Energy (DOE) by LLNL under contract DE-AC52-07NA27344. We acknowledge the modeling groups, the Program for Climate Model Diagnosis and Intercomparison, and the WCRP's Working Group on Coupled Modelling for their roles in making available the WCRP CMIP3 multimodel data set. Support of this data set is provided by the Office of Science, DOE.

Supporting Online Material

www.sciencemag.org/cgi/content/full/319/5863/607/DC1
SOM Text S1 to S5
Figs. S1 to S5
Tables S1 to S3
References

30 October 2007; accepted 18 December 2007
10.1126/science.1152339

Science

AAAS

www.sciencemag.org/cgi/content/full/319/5863/607/DC1

Supporting Online Material for

Prioritizing Climate Change Adaptation Needs for Food Security in 2030

David B. Lobell,* Marshall B. Burke, Claudia Tebaldi, Michael D. Mastrandrea, Walter P. Falcon, Rosamond L. Naylor

*To whom correspondence should be addressed. E-mail: dlobell@stanford.edu

Published 1 February 2008, *Science* **319**, 607 (2008)

DOI: 10.1126/science.1152339

This PDF file includes:

SOM Text S1 to S5
Figs. S1 to S5
Tables S1 to S3
References

Supplemental Material for Lobell et al. "Prioritizing climate change adaptation needs for food security in 2030"

Contents:

Text S1) Calculation of hunger importance rankings

The hunger importance (HI) was derived by multiplying estimates of the number of malnourished in each country within a region by the average per capita calories derived from each crop in that country, and then aggregating to the regional level (data from FAOSTAT, http://faostat.fao.org). Livestock products such as milk and meat were omitted. To ensure that crops in each region were of local origin (i.e. that produced crops were not exported, nor consumed crops imported), we generated a similar list of important crops using data on average per capita production volumes by country, and added to the original regional crop lists those crops unique to the production list – a step that rarely proved necessary.

Although using country-level average diets to represent the diets of the poorest ignores potentially large differences in diet composition across income classes – for example, diets of the poor in a given country are often richer in higher-starch, lower-value staples than their wealthier counterparts – to our knowledge no systematic data exist on consumption by region, crop, and income class. Nevertheless, the data suggest that even average diets exhibit large variation across regions. For example, in the Central Africa region, we calculate that the average calories derived from cassava are more than twice rice, wheat, and maize combined; in Southeast Asia, in contrast, rice alone accounts for roughly 60% of total calories consumed. Thus while the generated crop lists could misrepresent diets of the poorest, they pick up many of the crops traditionally associated with the poor, many of which have not been included in previous climate impact assessments. At the global level, the three main cereals (rice, maize, and wheat) account for only half of total calories consumed by the food insecure, while for Sub-Saharan Africa, where one-third of the population lives in chronic hunger, they account for just 31% of total calories (see Table S1).

A hunger importance ranking (HIR) was generated by ranking the HI values for all crop-by-region combinations. Using current data to construct the HIR raises the question of whether potential socioeconomic or agronomic shifts over the next 25 years might alter the diets or location of the global malnourished, and thus render the HI an implausible basis on which to formulate food security priorities for 2030. Various studies, for instance, predict that in coming decades Africa will account for a larger share of the global malnourished (S*1*), suggesting a ranking based on current hunger estimates could bias attention away from where it is most warranted. However, constructing an HIR based on FAO projections of regional malnourishment in 2030 under the assumption of no major shifts in diets yielded a 2030 HIR only slightly different from the 2003 ranking (see Table S2). Furthermore, our impact analysis is conducted and reported for all members of the HIR, and thus a simple re-ranking would be possible given preferred forecasts of regional shifts in hunger.

Text S2) Limitations of Crop Modeling Approaches

One approach to assessing crop impacts would be to synthesize existing studies (S2 *S3*); however they span a limited range of crops and regions, and many studies do not provide sufficient information to evaluate criteria (ii)-(iv). For example, many studies project impacts using a single GCM (S*4*, *S5*), thus neglecting a major source of uncertainty.

A second option would be to apply process-based crop models to evaluate impacts of climate change scenarios for the desired combinations of crops and regions (S*6*). However, the substantial time, data, and expertise needed to calibrate these models for particular locations (S*7,S8*) and the lack of process-based models for many minor crops, limit the utility of this approach.

A third option, which we employ here, is to develop statistical models of crop responses to climate change, based on historical datasets of crop and climate variables. Statistical crop models are prone to several deficiencies that should be understood when interpreting model results. First, our models rely on statistics for national area and production since 1961 produced by the Food and Agriculture Organization of the United Nations (FAO), which likely contain numerous errors, especially for minor crops. Second, it relies on gridded monthly climate data (S*9*) that may contain sizable errors in regions with relatively few weather stations. Errors in the climate variables - which are predictor variables in the statistical model - will tend to bias estimates of their effects toward zero, a phenomenon known as regression dilution (S*10*).

Third, yields and production have changed substantially since 1961 for most crops in most regions because of technological advances, such as the use of new varieties and greater application of fertilizers and irrigation, and expansion or contraction of harvested area. These technological and area trends can dominate the influence of other factors in determining long-term yield trends, and therefore analyses of climate effects must make some assumptions about the nature of these more gradual changes. Here, we use the common approach of converting all time series to first differences by subtracting the value from the prior year for each year from 1962-2002, which effectively dampens the influence of slowly varying factors (S*11*).

Fourth, building a statistical model from 43 years of data (1961-2002) necessitates the selection of relatively few predictor variables and model parameters to avoid model over-fitting. In the current study, we use a multiple linear regression (MLR) model with two climate variables: average temperature (T) and precipitation (P) for the crop's growing season. This procedure ignores the influence of climate variables other than growing season averages, such as rainfall in particular months or extreme rainfall or heat events. It also ignores potential non-linear effects of T or P on crop production (although including terms for the square of T and P did not significantly change results). In cases where these other climate variables are important, the relationship between growing season average T and P may be weak despite a real influence of climate on crop yields or production. Thus, as with regression dilution, there is a risk that model mis-specification will obscure climate effects that actually exist.

Fifth, statistical models are inherently limited to the range of conditions over which they are trained. For example, they cannot be extrapolated to predict production impacts for future temperatures that are higher than any historical year, without assumptions about the linearity of crop responses outside of the historical range. While this is a strong argument for using process-based models for end of 21st-century projections, extrapolation is less of an issue for 2030 when average projected temperatures are typically well below the warmest historical growing season (S*12*).

Despite these limitations, statistical models based on imperfect data represent, in our opinion, the best currently available means to evaluate the criteria outlined above for many crops and regions. As shown in the results, we find that these models can provide useful constraints on production responses to climate variations for many crop-region combinations. Where possible, we have also evaluated this approach by comparing model predictions with existing studies (Text S4).

Text S3) Data and Methods for Crop Models

A growing season for each crop in each region, defined as the months between planting and harvest of a given crop for those countries contributing the bulk of production in a given region, was derived from available sources (S*13*-*S17*) (See Figure S2) Sensitivity of results to the definition of growing season is discussed in the results section and shown in Figure S5.

Average historical temperature and precipitation for the growing seasons were generated from the 0.5º x 0.5º gridded monthly datasets produced by the Climate Research Unit of the University of East Anglia (CRU TS2.1), which spans 1901-2002 (S*9*). The CRU data were averaged temporally over the growing season months and spatially according to the geographic distribution of crop area from Leff et al. (S*18*), who generated maps for 18 major crops. In this manner, the temperature and precipitation specific to the location where and time of year when each crop is grown was obtained, an important step in building accurate statistical models (S*19*).

National data on total production and harvested area for 1961-2002 from FAO's Statistical Databases (S*20*) were summed for each study region to provide regional time series of production, area, and yield (computed as production divided by area). For South Asia, rice data for 2002 appeared anomalously low and was omitted from the analysis. The crop and climate time series were then combined to generate a statistical model for each crop as follows: (1) a first-difference time series was computed for each variable; (2) a MLR model was computed with crop production as the response variable and temperature and precipitation as predictors; (3) a corresponding MLR model was computed with crop yield as the response variable; (4) the model with the higher R^2 was selected for the crop. We did not choose *a priori* a model based on production or yield because different situations were suited to different variables. In particular, yield was more appropriate in cases where production changes were often unrelated to climate due to large and often nonlinear shifts in crop area. In contrast, production was more appropriate in cases where area changes were closely tied to climate, such as in Southeast Asia rice where sown area is heavily influenced by ENSO-related rainfall (S*21*).

Text S4) Comparison of estimated temperature sensitivities with previous studies

Table S3 compares temperature sensitivities estimated by the statistical models with corresponding values from previous studies that relied on established process-based models within the same regions. Comparisons were possible mainly for wheat, rice, and maize, given the lack of modeling studies for other crops. In cases where multiple previous studies were available for a single crop and location (e.g. rice or wheat in South Asia), considerable spread was evident between studies, demonstrating sizeable uncertainties in process-based model estimates themselves despite a failure of most modeling studies to quantify these uncertainties.

For all crops, statistical estimates generally overlapped the lower end of the range of previous estimates. A notable exception was the estimate for maize in Southern Africa, which in the current study was roughly two standard deviations above an estimate from a previous study in Zimbabwe. However, this discrepancy is likely in part explained by a scale mis-match between the current and previous study, as Zimbabwe comprises only ~3% of maize production in this region.

Differences between the statistical and process-based model estimates may similarly be attributable to scale in other cases, but a lack of harvest records at fine scales or simulation studies at broad scales makes it difficult to evaluate this factor. In one study that did focus on the same scale, Lobell and Ortiz-Monasterio (S*22*) found that statistical and CERES-wheat model predictions of temperature response in Northwest Mexico agreed to within a few percent (note that the statistical model estimate for Central American wheat in the current study is substantially smaller.) The relatively small estimates from the statistical models are also likely due to regression dilution, as discussed above, with errors in the climate data or definition of growing seasons biasing the estimates toward zero. The impacts estimated by the statistical models may therefore be considered conservative, but in reasonable agreement with estimates from process-based approaches.

Text S5) Caveats

The statistical crop models developed in this study, in combination with the database of multi-model climate projections, allowed the evaluation of climate change impacts across a broad range of crops and regions in a systematic, probabilistic, and transparent way, which in turn provides a means to identify “hotspots” of climate impacts in 2030 that can guide adaptation efforts. However, projections are inherently tied to the assumptions of the underlying models, and the potential sensitivity of results to these assumptions is thus important to understand. We consider several such assumptions below:

(i) The statistical crop models assume that growing season climate has been perfectly measured, whereas errors in CRU data and growing season definitions almost certainly exist. These errors will tend to result in overly-conservative estimates of impacts because of regression dilution (S9), and these effects will be strongest in regions with the poorest quality of climate data. To evaluate sensitivity to growing season definitions, the impact projections were repeated using three separate perturbations to the baseline growing season (see Figure S5 in supporting online material). The resulting changes were small for most crops, in particular those identified in Table 2. Therefore, our conclusions do not appear very sensitive to possible errors in growing season definition.

(ii) Roughly half of the models were not statistically significant (Table 1), indicating situations where growing season climate was a poor predictor of crop production. Several regions (e.g., South Asia, Southern Africa, Sahel) possessed many crops with high R^2, while in other regions relatively few crops were modeled well (e.g., East and Central Africa, Andean Region). These latter cases likely arise from some combination of poor harvest or climate data, importance of climate variables not highly correlated with growing season averages, and importance of factors not directly related to weather (e.g., prices, military conflicts, pest infestations). Thus, the statistical approach used here may be biased against regions with especially poor quality datasets or with especially high sensitivity to extreme climate events. The relatively small impacts projected for many crops in West, Central, and East Africa, for example, may result more from data and model errors than from actual low sensitivities to climate change, although it is difficult to distinguish these factors with the datasets used in this study. For crops with low model R^2, additional assessments using local expertise, country literature, and/or validated process-based models would therefore be especially useful.

(iii) Climate change uncertainty was represented by using equally weighted projections from 20 current GCMs. While this is a common approach, there is little theoretical basis for believing this accurately represents a true probability distribution. For example, some have argued that true uncertainties in rainfall projections are much larger than implied by the range of projections from current models (10).

(iv) The statistical crop models assume no adaptation to climate change, beyond that which takes place in response to year-to-year weather variations. Each cropping system undoubtedly has some internal mechanisms that will help it respond to climate change in the absence of intervention (i.e. autonomous adaptation). This adaptive capacity likely varies between the crops and regions studied here, just as it varies widely between developed and developing countries (1). Therefore, in defining needs for future investment, one should consider autonomous adaptation in addition to projected impacts without adaptation. This is especially true when considering longer time scales (e.g.,

2100) when systems will certainly recognize and respond to climate change, but may also be an important factor over the relatively short-term of the next few decades.

One aspect of adaptive capacity is the amount of research currently being conducted on the crop of interest. Several of the cases identified in Table 2 involve major commodities (i.e., wheat, maize, and rice) that benefit from major international research efforts on crop breeding and management improvement, including the maintenance of large gene banks. In contrast, other crops are relatively under-studied (i.e., millet, sorghum, rapeseed, groundnut) despite – or arguably because – of their unique importance to food insecure societies, which will diminish their adaptive capacity relative to the major crops. Thus, we argue that these less studied crops may require relatively more resources for adaptation.

(v) The impact projections ignored potential fertilization effects of elevated atmospheric CO_2 on crop yields. For the expected ~100 ppm increase from 1990 to 2030, a ~7% yield increase for crops with the C3 photosynthetic pathway can be expected (S11, S12). However, these effects will be similar for different C3 crops, and therefore should not affect relative priorities. In contrast, yields of C4 crops considered here (maize, sorghum, and sugarcane) will likely exhibit a negligible response to elevated CO_2. Yield losses relative to C3 crops will therefore be greater than suggested in Figure 3, placing a relatively greater emphasis on adapting C4 crops.

Table S1) Average crop contribution to total calories consumed by food insecure populations. This was computed by multiplying the number of malnourished in each country by the percent contribution of the crop to total consumed calories in that country, and then summing these values for the entire world (left), Sub-Saharan Africa (middle), or South Asia (right). All data was obtained from the FAO (http://faostat.fao.org).

	World			Sub-Saharan Africa			South Asia		
Rank	Crop	% of Total Calories	Cumulative %	Crop	% of Total Calories	Cumulative %	Crop	% of Total Calories	Cumulative %
1	rice	28.6%	28.6%	cassava	18.0%	18.0%	rice	29.6%	29.6%
2	wheat	18.7%	47.3%	maize	17.0%	35.0%	wheat	23.9%	53.5%
3	sugar cane	9.2%	56.5%	wheat	8.0%	43.0%	sugar cane	15.1%	68.6%
4	maize	7.3%	63.8%	sorghum	8.0%	51.0%	palm nuts	3.7%	72.3%
5	cassava	4.8%	68.6%	rice	6.0%	57.0%	millet	3.1%	75.4%
6	palm nuts	3.0%	71.6%	millet	4.0%	61.0%	groundnuts	2.3%	77.7%
7	soybeans	2.9%	74.5%	sugarcane	4.0%	65.0%	maize	2.3%	80.0%
8	sorghum	2.5%	77.0%	groundnuts	4.0%	69.0%	sorghum	2.1%	82.1%
9	groundnuts	2.4%	79.4%	palm nuts	4.0%	73.0%	soybeans	1.8%	83.9%
10	millet	2.0%	81.4%	beans	3.0%	76.0%	rapeseed	1.7%	85.6%
11	potatoes	2.0%	83.4%	plantains	2.0%	78.0%	chickpeas	1.7%	87.3%
12	beans and cowpeas	1.3%	84.7%	cereals nec	2.0%	80.0%	potatoes	1.6%	88.9%
13	sweet potatoes	1.2%	85.9%	sweet potatoes	2.0%	82.0%	pulses	1.3%	90.2%
14	barley	1.0%	86.9%	barley	2.0%	84.0%	coconuts	1.1%	91.3%
15	rapeseed	0.9%	87.8%	yams	2.0%	86.0%	beans and cowpeas	0.9%	92.2%

Table S2) Sensitivity of hunger importance ranking to projections of future number and locations of malnourished in 2030, which were derived from FAO (S*15*) by applying reported continent-wide or regional estimates of the percent change in number of hungry to each of our relevant smaller regions. Since no comprehensive region-level data exist on projected changes in diets to 2030, we assume no shifts in the diets of the hungry. Light blue indicates a fall in the hunger importance ranking by two places, dark blue a fall of more than five places, and red indicates increased hunger importance of at least two places.

Country	Crop	HIR, 2003	HIR, 2030
South Asia	rice	1	1
Southeast Asia	rice	2	3
South Asia	wheat	3	2
China	rice	4	5
South Asia	sugar cane	5	4
China	wheat	6	8
Central Africa	cassava	7	6
East Africa	maize	8	7
Southern Africa	maize	9	10
West Asia	wheat	10	9
East Africa	wheat	11	11
China	soybeans	12	18
Southeast Asia	sugar cane	13	19
South Asia	millet	14	14
Southern Africa	cassava	15	12
East Africa	cassava	16	13
Southeast Asia	wheat	17	27
Central Africa	maize	18	15
Sahel	sorghum	19	16
East Africa	sorghum	20	17
Central America and Caribbean	maize	21	23
South Asia	groundnuts	22	20
China	sugar cane	23	33
South Asia	maize	24	21
South Asia	sorghum	25	24
China	potatoes	26	39
China	sweetpotatoes	27	40
South Asia	soybeans	28	29
China	groundnuts	29	44
South Asia	rapeseed	30	32

Table S3. Comparison of estimated crop sensitivities to 1.0 ºC temperature increase in the current study and in previous modeling studies.

Region	Crop	%Yield Change per 1.0 ºC, current study [a]	Reference	Model Used	Location	%Yield Change per 1.0 ºC [b]
South Asia	Rice	-4.0 ± 2.0	(S*24*)	CERES-Rice	NW India	-10
			(S*25*)	CERES-Rice	India	-6
			(S*26*)	CERES-Rice	India	-10 - -2.5
	Wheat	-2.6 ± 0.7	(S*24*)	CERES-Wheat	NW India	-13
			(S*27*)	CERES-Wheat	NW India	-9 – -3
			(S*28*)	CERES-Wheat	Pakistan	-17 - -7
			(S*29*)	CERES-Wheat	India	-15
	Maize	-4.8 ± 3.7	(S*30*)	CERES-Maize	India	-8
Southeast Asia	Rice	-1.4 ± 0.8	(S*31*)	CERES-Rice	Bangladesh	-9 - -4
			(S*32*)	CERES-Rice	Philippines	-14 - -8
			(S*33*)	CERES-Rice	Thailand	-14 - -12
Southern Africa	Maize	-21.4 ± 8.6	(S*34*)	CERES-Maize	Zimbabwe	-7 - -4
Central America	Wheat	-5.1 ± 1.8	(S*22*)	CERES-Wheat	NW Mexico	-12 - -7
	Maize	-0.6 ± 1.9	(S*35*)	CERES-Maize	Mexico	-5
Brazil	Wheat	-7.1 ± 2.4	(S*36*)	CERES-Wheat	Brazil	-16 - -9
	Maize	-2.4 ± 2.5	(S*36*)	CERES-Maize	Brazil	-8 - -4
	Soybean	-4.5 ± 3.9	(S*36*)	SOYGRO	Brazil	-6 - +3

[a] coefficient for temperature in yield regression model (mean ± 1 standard deviation)
[b] range shows values for different sites or management levels, when available

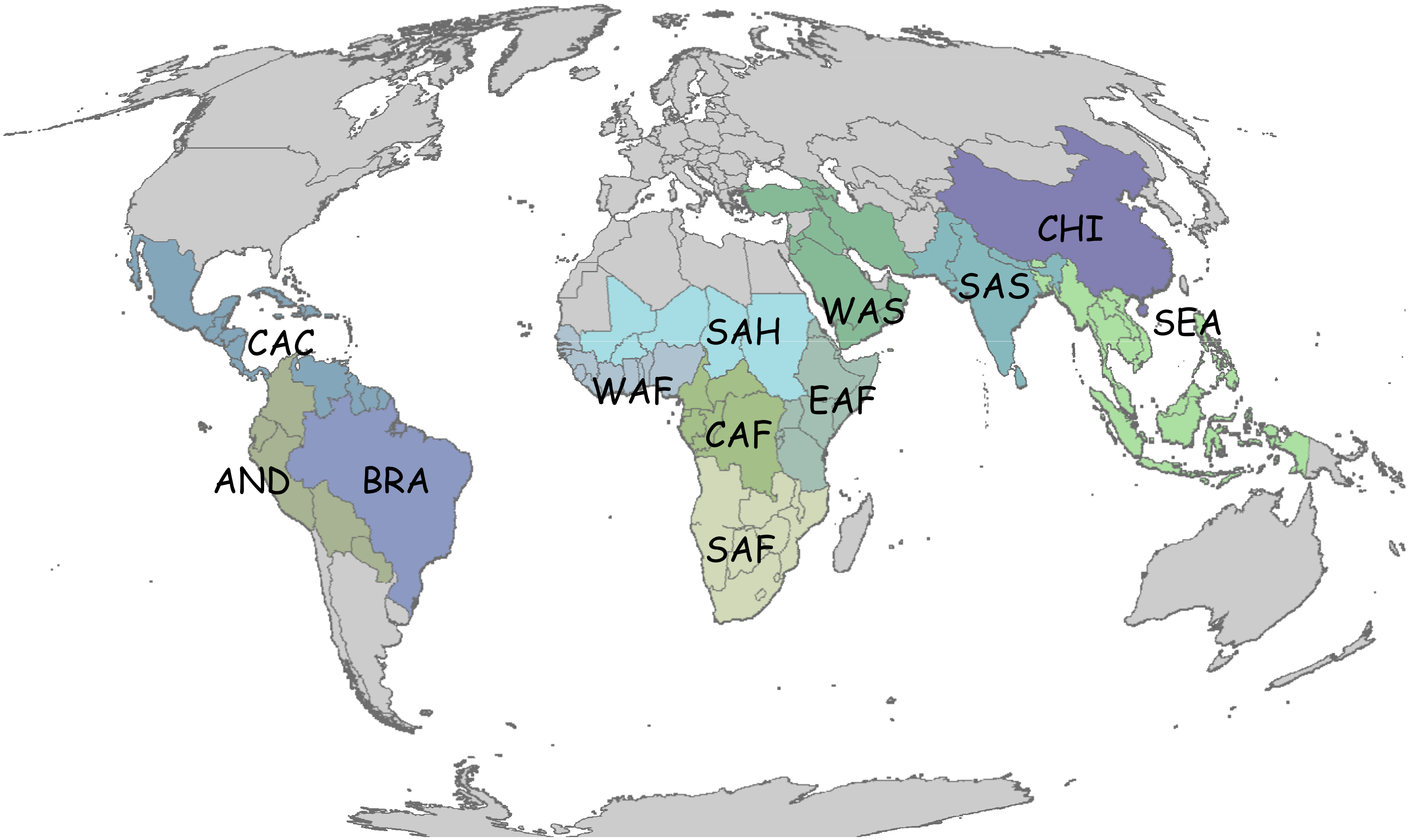

Figure S1) Definition of 12 Study Regions.

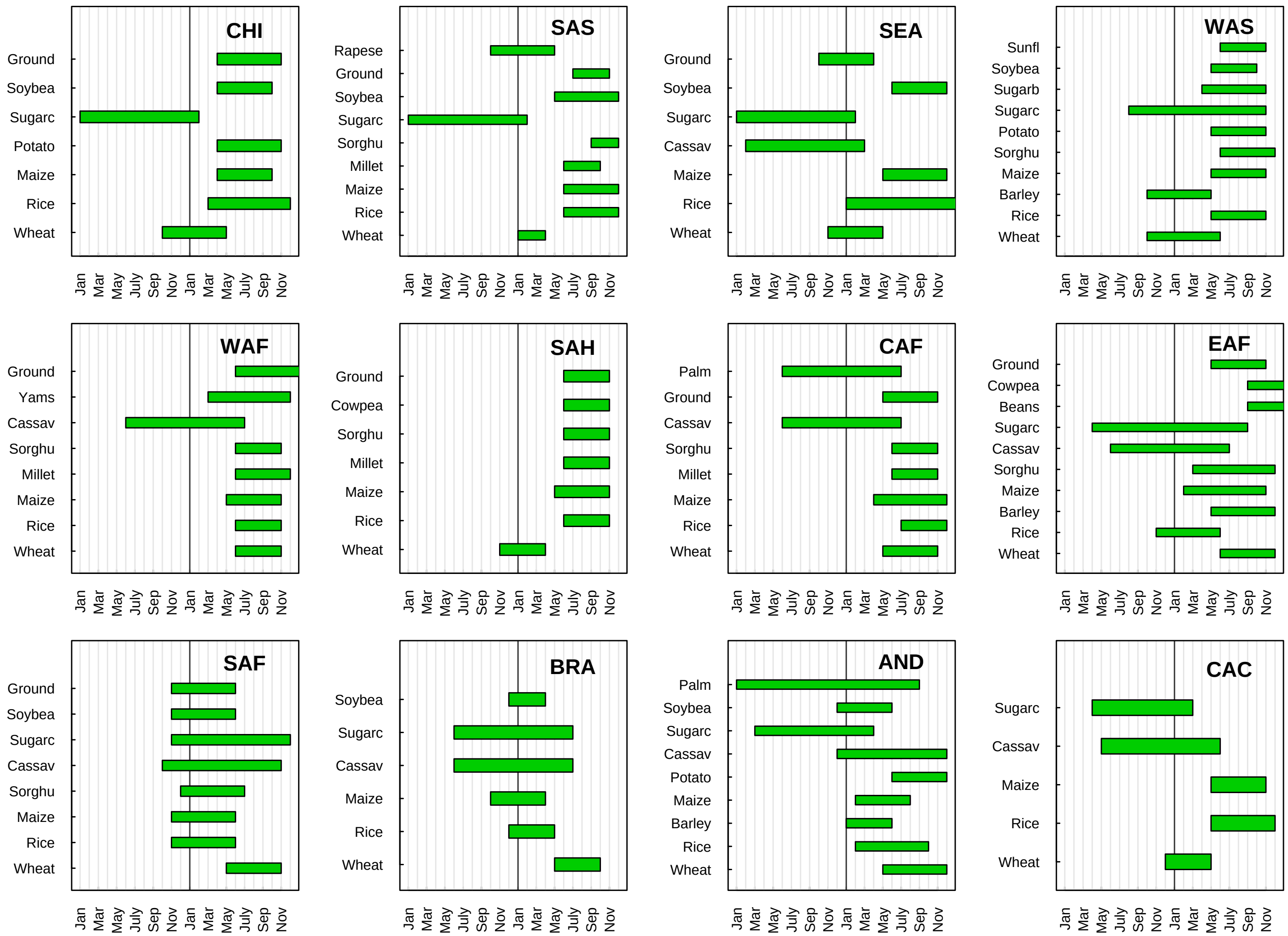

Figure S2) Growing seasons used for each crop. X-axis spans 24 months from January of year prior to harvest to December of harvest year.

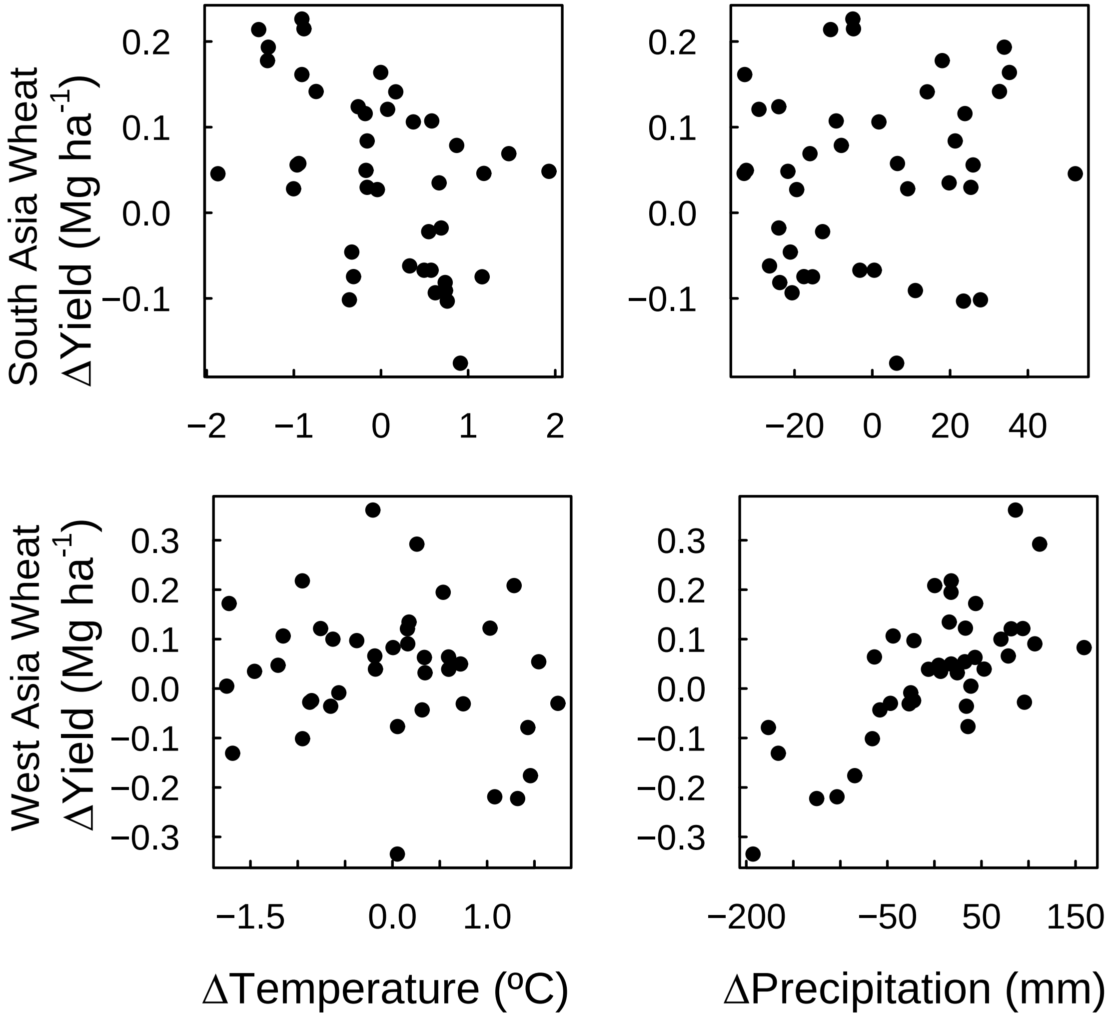

Figure S3) First differences of wheat yields in South Asia (top) and West Asia (bottom) plotted against temperature and precipitation.

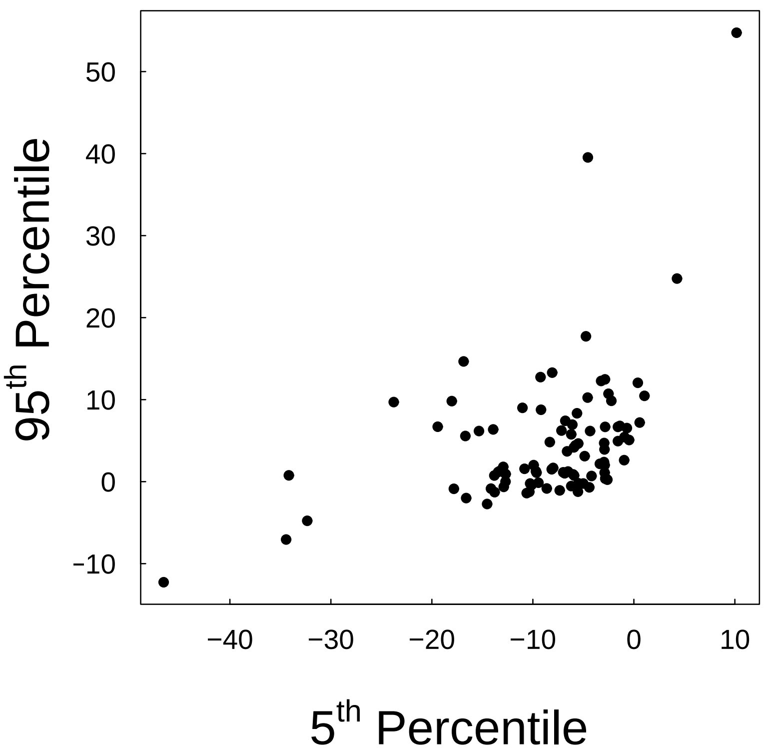

Figure S4) Comparison of extreme percentiles from climate change impact projections for 94 crops. Each point indicates the 5th (C05) and 95th (C95) percentile of projected impacts for a single crop. While the crops with low C05 tend to have low C95, the two are not tightly correlated, reflecting the varying degree of uncertainty for different crops.

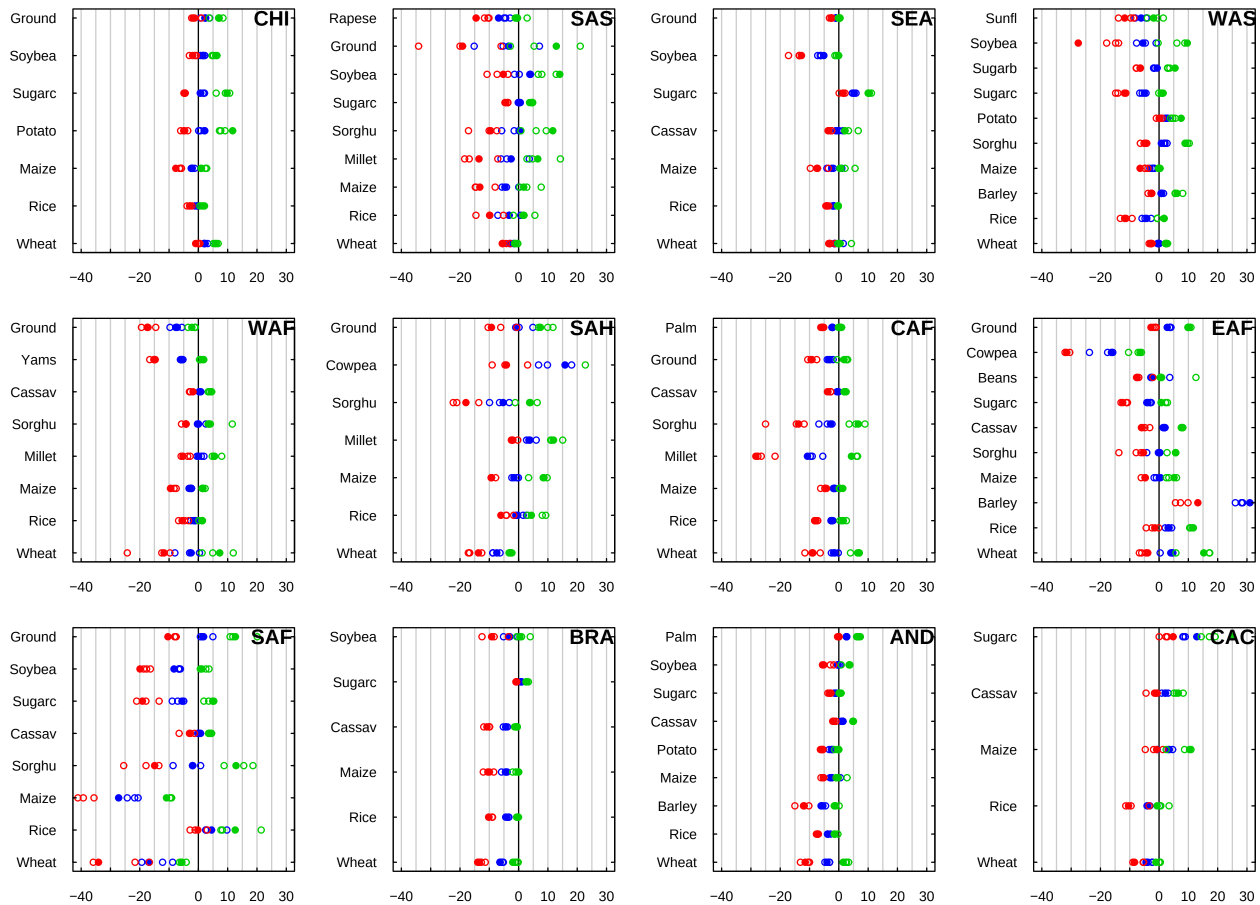

Figure S5) Sensitivity of impact estimates to definition of growing season. Points indicate 5th (red) 50th (blue) and 95th (green) percentile of projections when using baseline growing seasons (solid points) and other definitions of growing seasons (open points). Three alternatives were tested: shift growing season earlier by 1 month, shift later by 1 month, or narrow growing season by removing first and last months. In most cases, the crops identified as most important do not appear very sensitive to exact growing season definition.

References:

S1. M. Rosegrant, M. Paisner, S. Meijer, J. Witcover, "Global food projections to 2020: Emerging trends and alternative futures" (International Food Policy Research Institute, 2001).

S2. W. Easterling *et al.*, in *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. (Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA., 2007).

S3. W. R. Cline, *Global Warming and Agriculture: Impact Estimates by Country*. (Center for Global Development, Washington, D.C., 2007), pp. 250.

S4. J. O. Adejuwon, *Clim Res* **32**, 229 (2006).

S5. P. G. Jones, P. K. Thornton, *Global Environmental Change-Human and Policy Dimensions* **13**, 51 (Apr, 2003).

S6. C. Rosenzweig, M. L. Parry, *Nature* **367**, 133 (1994).

S7. C. Rosenzweig, A. Iglesias, Eds., *Implications of climate change for international agriculture: crop modeling study*, (United States Environmental Protection Agency, Washington, D.C., 1994), pp. 466.

S8. D. Wallach, D. Makowski, J. Jones, Eds., *Working with Dynamic Crop Models - Evaluation, Analysis, Parameterization, and Applications*, (Elsevier, Amsterdam, The Netherlands, 2006), pp. 462.

S9. T. D. Mitchell, P. D. Jones, *Int. J. Clim.* **25**, 693 (May, 2005).

S10. C. Frost, S. G. Thompson, *Journal of the Royal Statistical Society: Series A (Statistics in Society)* **163**, 173 (2000).

S11. N. Nicholls, *Nature* **387**, 484 (May, 1997).

S12. D. B. Lobell, C. B. Field, K. N. Cahill, C. Bonfils, *Agric For Meteorol* **141**, 208 (2006).

S13. FAO, "Crop calendars for African countries" (1997).

S14. FAO, "Irrigation cropping calendar per country" http://www.fao.org/ag/agl/aglw/aquastat/water_use/index.stm (2007). Accessed

S15. USDA, *Major world crop areas and climatic profiles (revised). United States Deparment of Agriculture, Agricultural Handbook No. 664* (Washington, D.C., 1994), pp. 279.

S16. USDA, "Crop Calendar Indexes" http://www.fas.usda.gov/remote/aus_sas/crop_information/calendars/index_of_clndrs.htm (2003). Accessed May, 2007

S17. International Rice Research Institute, "Atlas of Rice and World Rice Statistics" http://www.irri.org/science/ricestat/ (2007). Accessed May 2007

S18. B. Leff, N. Ramankutty, J. A. Foley, *Global Biogeochemical Cycles* **18**, GB1009 (Jan, 2004).

S19. D. B. Lobell, C. B. Field, *Environmental Research Letters* **2**, 004000 (7pp) (2007).

S20. FAO, "Food and Agriculture Organization of the United Nations (FAO), FAO Statistical Databases" http://faostat.fao.org (2007). Accessed

S21. R. Naylor, W. Falcon, N. Wada, D. Rochberg, *Bulletin of Indonesian Economic Studies* **38**, 75 (2002).
S22. D. B. Lobell, J. I. Ortiz-Monasterio, *Agron J* **99**, 469 (February 6, 2007, 2007).
S23. FAO, *World agriculture towards 2030/2050, Interim Report. Food and Agricultural Organization of the United Nations*. (Rome, Italy, 2006).
S24. M. Lal, K. K. Singh, L. S. Rathore, G. Srinivasan, S. A. Saseendran, *Agric For Meteorol* **89**, 101 (1998).
S25. S. A. Saseendran, K. K. Singh, L. S. Rathore, S. V. Singh, S. K. Sinha, *Clim Change* **44**, 495 (2000).
S26. R. K. Mall, P. K. Aggarwal, *Clim Change* **52**, 315 (Feb, 2002).
S27. S. D. Attri, L. S. Rathore, *Int. J. Clim.* **23**, 693 (2003).
S28. A. Qureshi, A. Iglesias, in *Implications of climate change for international agriculture: crop modeling study,* C. Rosenzweig, A. Iglesias, Eds. (United States Environmental Protection Agency, Washington, D.C., 1994), pp. 466.
S29. D. G. Rao, S. K. Sinha, in *Implications of climate change for international agriculture: crop modeling study,* C. Rosenzweig, A. Iglesias, Eds. (United States Environmental Protection Agency, Washington, D.C., 1994), pp. 466.
S30. R. K. Mall, R. Singh, A. Gupta, G. Srinivasan, L. S. Rathore, *Clim Change* **78**, 445 (2006).
S31. Z. Karim, M. Ahmed, S. G. Hussain, K. B. Rashid, in *Implications of climate change for international agriculture: crop modeling study*, C. Rosenzweig, A. Iglesias, Eds. (United States Environmental Protection Agency, Washington, D.C., 1994), pp. 466.
S32. C. R. Escaño, V. Buendia, in *Implications of climate change for international agriculture: crop modeling study,* C. Rosenzweig, A. Iglesias, Eds. (United States Environmental Protection Agency, Washington, D.C., 1994), pp. 466.
S33. C. Tongyai, in *Implications of climate change for international agriculture: crop modeling study,* C. Rosenzweig, A. Iglesias, Eds. (United States Environmental Protection Agency, Washington, D.C., 1994), pp. 466.
S34. P. Muchena, in *Implications of climate change for international agriculture: crop modeling study,* C. Rosenzweig, A. Iglesias, Eds. (United States Environmental Protection Agency, Washington, D.C., 1994), pp. 466.
S35. D. Liverman, M. Dilley, K. O'Brien, L. Menchaca, in *Implications of climate change for international agriculture: crop modeling study*, C. Rosenzweig, A. Iglesias, Eds. (United States Environmental Protection Agency, Washington, D.C., 1994), pp. 466.
S36. O. d. Siqueira, J. Farias, L. Sans, in *Implications of climate change for international agriculture: crop modeling study,* C. Rosenzweig, A. Iglesias, Eds. (United States Environmental Protection Agency, Washington, D.C., 1994), pp. 466.