Environ. Res. Lett. **3** (2008) 034007 (8pp) doi:10.1088/1748-9326/3/3/034007

Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation

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Received 24 June 2008
Accepted for publication 27 August 2008
Published 11 September 2008
Online at stacks.iop.org/ERL/3/034007

Abstract
Estimates of climate change impacts are often characterized by large uncertainties that reflect ignorance of many physical, biological, and socio-economic processes, and which hamper efforts to anticipate and adapt to climate change. A key to reducing these uncertainties is improved understanding of the relative contributions of individual factors. We evaluated uncertainties for projections of climate change impacts on crop production for 94 crop–region combinations that account for the bulk of calories consumed by malnourished populations. Specifically, we focused on the relative contributions of four factors: climate model projections of future temperature and precipitation, and the sensitivities of crops to temperature and precipitation changes. Surprisingly, uncertainties related to temperature represented a greater contribution to climate change impact uncertainty than those related to precipitation for most crops and regions, and in particular the sensitivity of crop yields to temperature was a critical source of uncertainty. These findings occurred despite rainfall's important contribution to year-to-year variability in crop yields and large disagreements among global climate models over the direction of future regional rainfall changes, and reflect the large magnitude of future warming relative to historical variability. We conclude that progress in understanding crop responses to temperature and the magnitude of regional temperature changes are two of the most important needs for climate change impact assessments and adaptation efforts for agriculture.

Keywords: global warming, food production, sensitivity analysis

1. Introduction

Rainfall is extremely important to agriculture. Historically, many of the biggest shortfalls in crop production have resulted from droughts caused by anomalously low precipitation [1, 2]. At the same time, predicting regional responses of precipitation to anthropogenic greenhouse gases has proven a very difficult task, with leading climate models often disagreeing on the sign of precipitation change [3]. These two widespread observations have led many to assume that improved rainfall projections represent a key bottleneck to reducing uncertainties in projections of climate change impacts on agriculture. For example, many have argued that climate model downscaling to improve regional hydrological projections is among the most urgent needs for agriculture [4, 5].

However, arguments have also been made for the importance of other possible research directions, such as improved treatment of extreme events [6, 7], more experimental tests of CO_2 fertilization effects [8], and better understanding of crop temperature response [9, 10]. Although all of these certainly have some merit, little work has been done to compare the relative contribution of these and other factors to uncertainties in current projections, and therefore little objective basis exists for prioritizing research efforts. Knowledge of which specific factors give rise to the bulk of

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uncertainty is therefore a critical step toward reducing overall uncertainty in projections [9, 11, 12].

To evaluate sources of uncertainty, we begin with a simple but useful approximation for the change in crop production (ΔY) that results from a given change in growing season average temperature (ΔT) and precipitation (ΔP):

$$\Delta Y = \beta_T \Delta T + \beta_P \Delta P \quad (1)$$

where β_T and β_P represent the sensitivity of crop production to temperature and precipitation, respectively. This equation ignores other aspects of climate change and potential nonlinear effects of temperature or precipitation, such as those that arise from extreme heat waves [7] or interactions with other variables, but represents a useful first-order estimate for changes over the next few decades. In addition, results from these simple statistical models are broadly consistent with those from studies that used process-based models, as described below. If uncertainties in $\beta_{\mathrm{T}}, \Delta T$, β_P, and ΔP are independent, then uncertainty in ΔY can be expressed as [13]:

$$\begin{aligned} \mathrm{Var}(\Delta Y) &= \mathrm{Var}(\beta_T \Delta T + \beta_P \Delta P) = E[\beta_T]^2 \mathrm{Var}(\Delta T) \\ &\quad + E[\Delta T]^2 \mathrm{Var}(\beta_T) + \mathrm{Var}(\beta_T)\mathrm{Var}(\Delta T) \\ &\quad + E[\beta_P]^2 \mathrm{Var}(\Delta P) + E[\Delta P]^2 \mathrm{Var}(\beta_P) \\ &\quad + \mathrm{Var}(\beta_P)\mathrm{Var}(\Delta P) \end{aligned} \quad (2)$$

where $E[\ ]$ denotes the expected value and $\mathrm{Var}(\ )$ denotes variance.

2. Methods

We evaluated each term in equation (2) for projections of climate change impacts by 2030 for crops and regions considered in a recent analysis focused on food security [14], with a total of 94 crop–region combinations. Values for $E[\Delta T]$, $E[\Delta P]$, $\mathrm{Var}(\Delta T)$, and $\mathrm{Var}(\Delta P)$ were computed from projections for 20 different general circulation models (GCMs) that participated in the fourth assessment report of the Intergovernmental Panel on Climate Change, using three emissions scenarios (SRES B1, A1b, and A2). Each model possesses quasi-independent representations of atmosphere, land, and ocean dynamics, and therefore the variance of projections between models represents a common measure of uncertainty related to these dynamics. Changes by 2030 were computed as averages for 2020–2039 minus averages for 1980–1999.

Values for $E[\beta_T]$, $E[\beta_P]$, $\mathrm{Var}(\beta_T)$, and $\mathrm{Var}(\beta_{\mathrm{P}})$ were computed from statistical models based on historical data for crop production from the Food and Agriculture Organization (FAO; http://faostat.fao.org) and temperature and rainfall from the Climate Research Unit (CRU TS2.1) [15]. The details of the regression models are provided in Lobell *et al* [14]. Briefly, for each crop–region combination time series of growing season T and P for 1961–2002 were computed by averaging monthly values in the CRU dataset for the growing season months and for the locations where the crop is grown, based on maps of individual crop areas [16]. The growing season T and P averages and annual crop production from FAO were transformed to first-differences to remove trend components, and then a multiple linear regression with production as the response and T and P as the predictors was computed.

To evaluate whether the assumption in equation (2) that uncertainties in ΔT and ΔP are independent was valid, we computed the correlation between model projections of ΔT and ΔP for each crop–region combination. All 94 values were below 0.5 in absolute value, with an average squared correlation of $R^2 = 0.06$. Thus, consideration of covariance between temperature and precipitation uncertainties would not appreciably change the results presented below.

Another important consideration is whether equation (1) accurately describes the relationship between weather and crop production. One measure of this is the R^2 of the model, which varied from a low of near zero to a high of 0.67 for South Asia groundnuts. An R^2 of 0.67 indicates that a linear model using growing season temperature and rainfall is able to explain two-thirds of the variation in crop production, and thus inclusion of nonlinear terms or other climatic variables is not needed to predict the majority of yield variation. Note this does not preclude some role for nonlinearities, but simply says that the majority of yield variation is driven by change in growing season averages. In contrast, a low R^2 indicates that these other terms may be important, that crop harvests vary less according to weather than to other abiotic or biotic stresses, and/or that reported harvests contain large amounts of noise. The patterns of R^2 give some insight into the causes for low R^2. For example, R^2 tends to be higher in some regions (e.g., Sahel, Southern Africa, South Asia) than others (e.g., Central and West Africa) and some crops (e.g. maize) than others (e.g. cassava), indicating that R^2 may reflect differences in the quality of data, characteristics of the climate systems, or growth traits of particular crops [14]. In contrast, factors such as irrigation or average yields do not appear strongly related to model R^2. The implications of low model R^2 for the conclusions of the current study are discussed below.

3. Results and discussion

Rainfall plays a critical role in year-to-year variability of production for these crops, with a change in growing season precipitation by one standard deviation associated with as much as a 10% change in production (in the case of South Asia millets; figure 1(a)). Temperature also plays a significant role in driving year-to-year production changes, but was slightly less important than rainfall by this measure in the majority of cases. This result agrees with the intuition that rainfall is very important to agriculture.

In contrast, the contribution of terms in equation (2) to total variance highlights a surprisingly dominant role of temperature (figure 1(b)). In figure 1(b), factors related to temperature (the first three terms in equation (2)) are shown in shades of red while those related to precipitation are shown in blue. Only in three cases among the top 20 crop–region combinations (rice and millet in South Asia and wheat in West Asia) do uncertainties associated with precipitation contribute more than 25% to total variance. The single biggest source of uncertainty in most cases is the second term, relating to uncertainty in the response of crop production to temperature

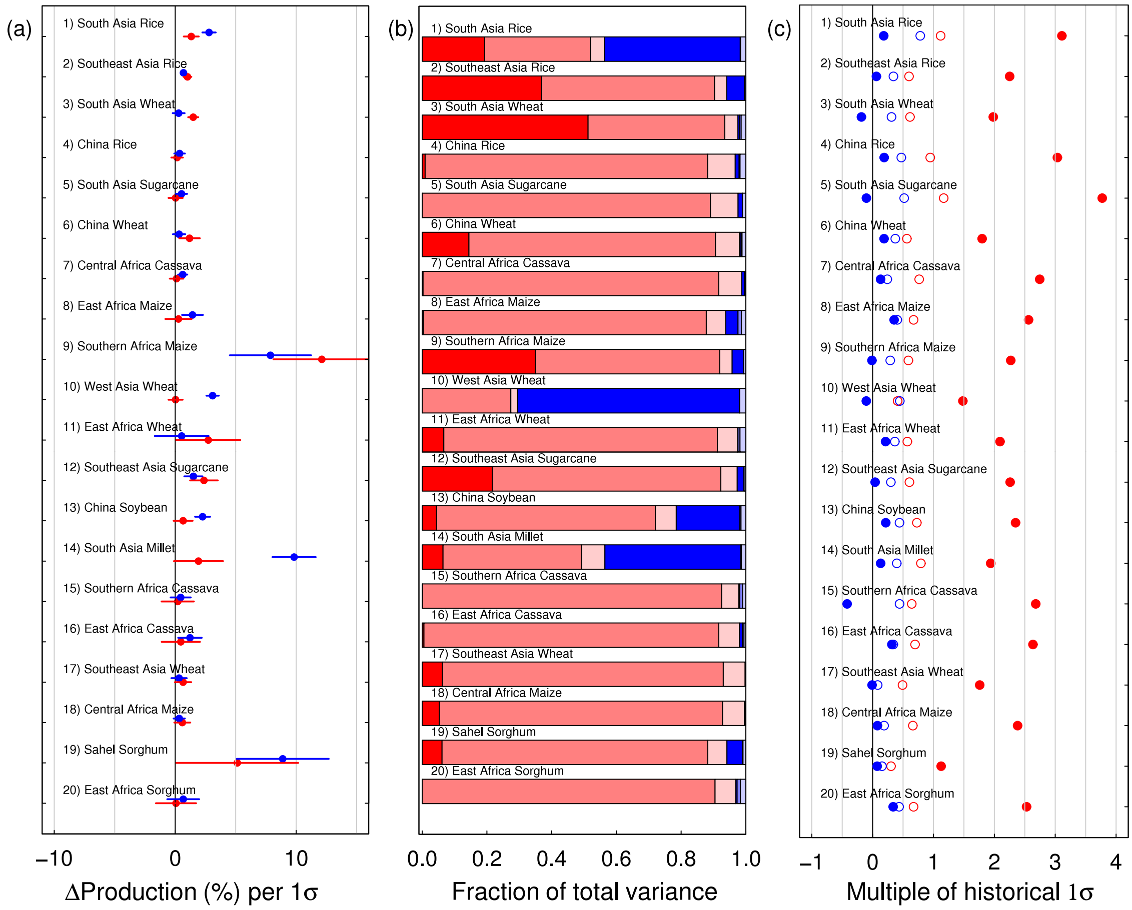

Figure 1. (a) The predicted response of crop production (% of 1998–2002 average production) to a change in growing season average temperature (red) or precipitation (blue) equivalent to one standard deviation of historical variability, shown for the top 20 crops most important to global food security [14]. Absolute values of coefficients are displayed to ease comparison of magnitudes, since most temperature coefficients are negative and most rainfall coefficients are positive. Error bars indicate $\pm 1\sigma$ of values of β_T and β_P. (b) The contribution of each term in equation (2) to total variance in climate change impact projections for 2030. All terms were normalized by the total variance, which varies by crop, so that the sum of the six terms equals one. Dark red = $E[\beta_T]^2 \mathrm{Var}(\Delta T)$, medium red = $E[\Delta T]^2\ \mathrm{Var}(\beta_T)$, light red = $\mathrm{Var}(\beta_T)\ \mathrm{Var}(\Delta T)$, dark blue = $E[\beta_P]^2\ \mathrm{Var}(\Delta P)$, medium blue = $E[\Delta P]^2\ \mathrm{Var}(\beta_P)$, light blue = $\mathrm{Var}(\beta_P)\ \mathrm{Var}(\Delta P)$. (c) Mean (solid) and standard deviation (open) of projections for growing season average temperature (red) and precipitation (blue) changes by 2030, based on output from 20 GCMs and expressed as a multiple of the standard deviation of historical temperature or precipitation.

change. This is true even in predominantly rainfed systems, such as most cases with maize, cassava, sorghum or millet. Temperature also appears to dominate regardless of whether the crop was irrigated or the whether it was grown in high or low yielding environment, with a correlation of 0.03 between average yields and the sum of temperature related factors in figure 1(b).

The unexpectedly small role of precipitation can be understood by closer examination of $E[\Delta T]$, $E[\Delta P]$, $\sigma(\Delta T)$, and $\sigma(\Delta P)$, which are expressed for each crop in figure 1(c) as a multiple of the historical standard deviation of growing season temperature (σ_T) or precipitation (σ_P). (We present standard deviations of projections (e.g., $\sigma(\Delta T)$) rather than variances to make all ratios unitless. Results were qualitatively similar when using ranges of projections rather than standard deviations.) Although values of $\sigma(\Delta P)$ are typically larger in absolute value than $E[\Delta P]$, which indicates that several models disagree on the sign of change, both values are typically less than 0.5 σ_P. Values of $E[\Delta T]$, in contrast, always exceed σ_T, with an average change of 2.3 σ_T by 2030 (solid red circles in figure 1(c)). The uncertainty surrounding temperature projections ($\sigma(\Delta T)$) is also larger relative to σ_T than in the case of $\sigma(\Delta P)$ and σ_P.

The simple interpretation of these results is that although the sign of precipitation change is most often unknown, climate models generally agree that the magnitude of change will not be very large relative to historical year-to-year variability, even if we consider models with the most extreme precipitation projections. In contrast, even the uncertainty surrounding temperature projections are large relative to historical variability, and the mean projected warming for 2030 is more than twice the historical standard deviation of temperature. These statements assume that the inter-model standard deviation of GCM projections is a fair representation of climate uncertainty, an assumption that has been widely challenged, particularly in the case of precipitation [17–19], in part on the grounds that different climate models are not independent. Nonetheless, even if the true uncertainties in future precipitation changes were twice as large as those estimated using inter-model differences, they would still

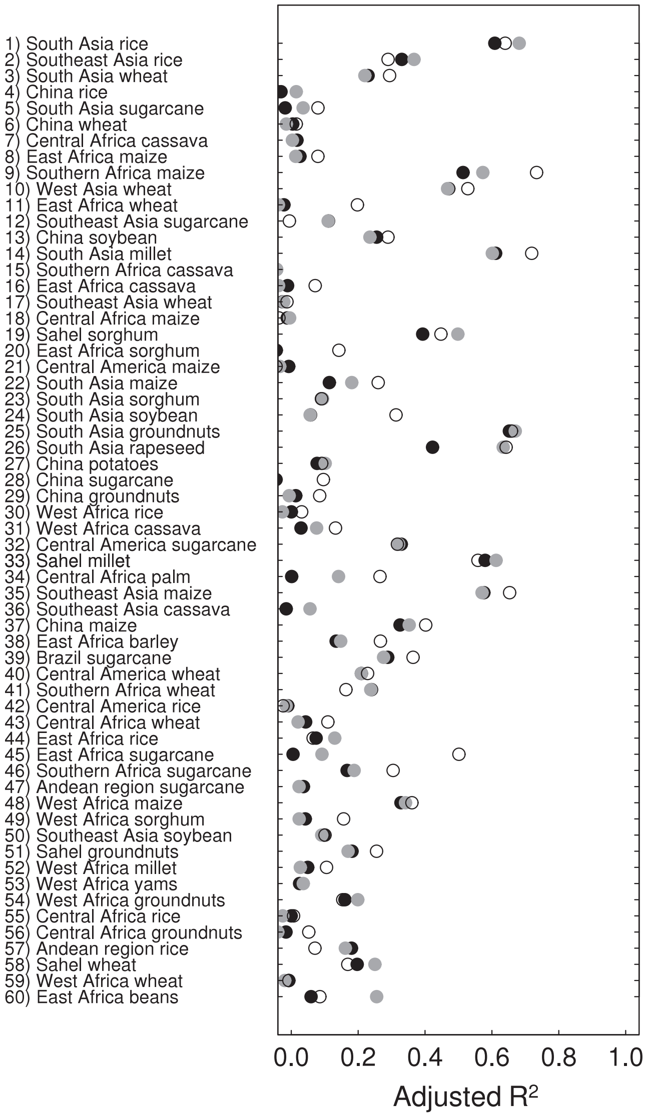

Figure 2. Summary of model fits to historical crop production and growing season climatic data for crop–region combinations, ranked by a measure of importance to global food security: model adjusted R^2 for original model (solid black), model with monthly precipitation (open black), and model with temperature–rainfall interaction term (gray). Adjusted R^2 accounts for the larger number of predictors when using monthly precipitation, which will tend to inflate the unadjusted R^2. (Adjusted $R^2 = 1 - (1 - R^2)^*(n-1)/(n-p-1)$, where n is total number of observations and p is number of predictors.)

represent a fairly small component of total uncertainty (see below).

In addition to errors in estimates of climate uncertainties, our estimates of crop responses and their uncertainties are prone to errors that could potentially bias the results. First, one could argue that the importance of rainfall to crops (β_P) relative to temperature is underestimated by using region and growing season averages. For example, it is possible that rainfall during critical stages of crop growth is both more important than, and poorly correlated with, average growing season rainfall. To test the importance of the intra-seasonal temporal distribution of rainfall, the average precipitation term

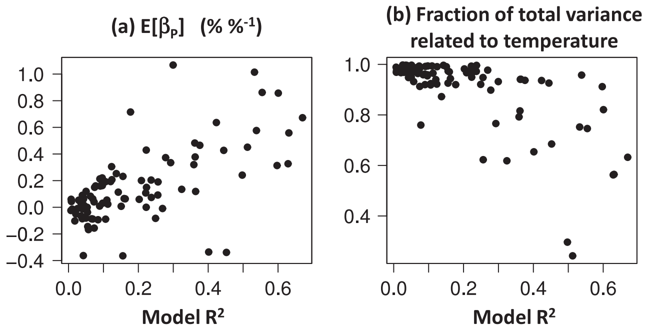

Figure 3. The relationship between the R^2 of the statistical crop model in each of 94 crop–region combinations and (a) the inferred sensitivity of crop production to precipitation, expressed as % change in production for each % change in precipitation, and (b) the fraction of total variance attributed to temperature related factors in equation (2). Models with higher R^2 tend to have greater sensitivity to precipitation and a more important contribution from rainfall to uncertainty in future impacts, although the role of temperature is still significant for several models with R^2 above 0.4.

in equation (1) was replaced with monthly precipitation for each month in the growing season and a new regression was computed. While the model R^2 improved in nearly all cases, the improvement in most cases was no more than expected by chance when adding additional predictors (five additional predictors in the case of a six month growing season), as judged by the adjusted R^2 (figure 2).

Another possible source of error is omission of important interactions between temperature and rainfall. To test this, a term was added to equation (1) to represent the interaction of precipitation and temperature [20]. Again, the R^2 increased in some cases (particularly in the case of South Asia rapeseeds), but overall the models were not substantially improved (figure 2).

The results therefore appear relatively insensitive to the specification of monthly rainfall or interactions in the model. Other sources of uncertainty are more difficult to directly evaluate, such as those that arise from spatial aggregation over diverse climates within mountainous countries such as Kenya and Tanzania, and those that arise from rainfall at sub-monthly timescales. One indication that estimates of $E[\beta_P]$ may be biased toward zero is that models with higher R^2 tended to have higher values of $E[\beta_P]$ (figure 3(a)). These models also tended to have a greater contribution of precipitation to total uncertainty, although uncertainties for many models with high R^2 were still dominated by temperature (figure 3(b)).

A more thorough sensitivity analysis of equation (2) was conducted to evaluate how far off the estimates of each variable in equation (2) could be before the results qualitatively changed. The empirical distributions of each variable across all 94 crop–region combinations are illustrated in figure 4, with the median value indicated by the thin vertical line. A two-at-a-time sensitivity analysis was conducted based on these distributions, with each term in equation (2) computed as two variables were systematically varied across the range of observed values, holding all other variables at their median value.

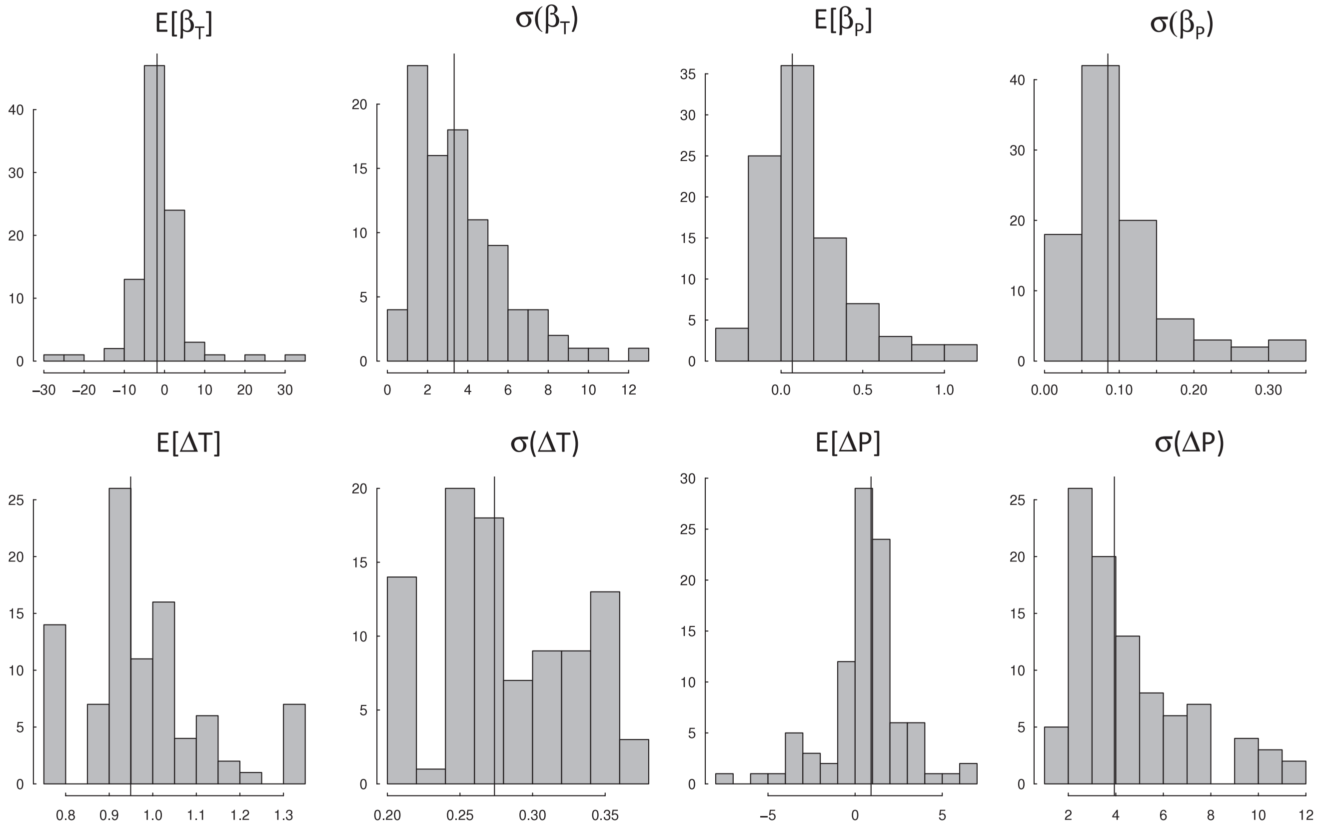

Figure 4. Histogram of the estimates for each variable in equation (2) from 94 crop–region combinations. Units are % per °C for β_T, % per % for β_P, °C for ΔT, and % for ΔP. Vertical solid line shows median value.

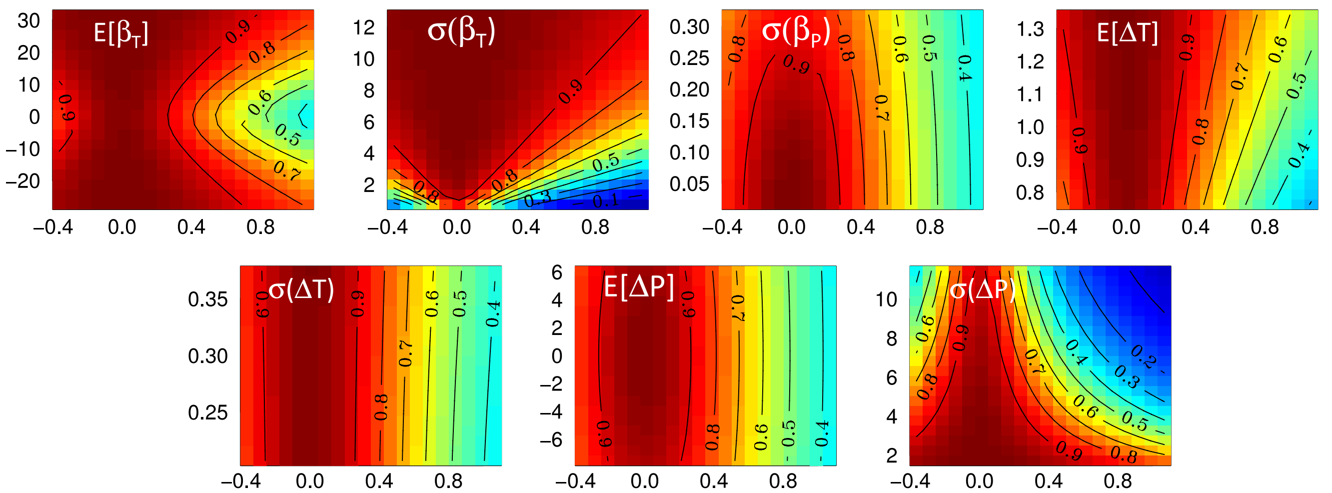

Figure 5. Sensitivity analysis of the fraction of total variance in equation (2) contributed by the first three terms relating to temperature. Each panel displays this fraction as β_P and one other variable are varied over the range of observed values, with all other variables fixed at their median values. The x-axis shows variation in β_P and the panel label indicates the variable on the y-axis. For most combinations, temperature terms contribute most of the total uncertainty.

Results indicated that the relative importance of terms involving temperature was most sensitive to the value of $E[\beta_P]$ (figure 5). Precipitation uncertainties became most important for high values of $E[\beta_P]$ coupled with low values of $E[\beta_T]$ and $\mathrm{Var}(\beta_T)$ and high values of $\mathrm{Var}(\Delta P)$. This result makes intuitive sense: in cases where crops are relatively sensitive to rainfall and future rainfall is very uncertain, then future impacts of climate change rest largely on impacts of rainfall changes. However, these situations are the exception rather than the rule, as indicated by the relatively small amount of the parameter space with more than half of total variance contributed by precipitation terms.

As another measure of robustness that considers all possible interactions not captured by two-at-a-time tests, we

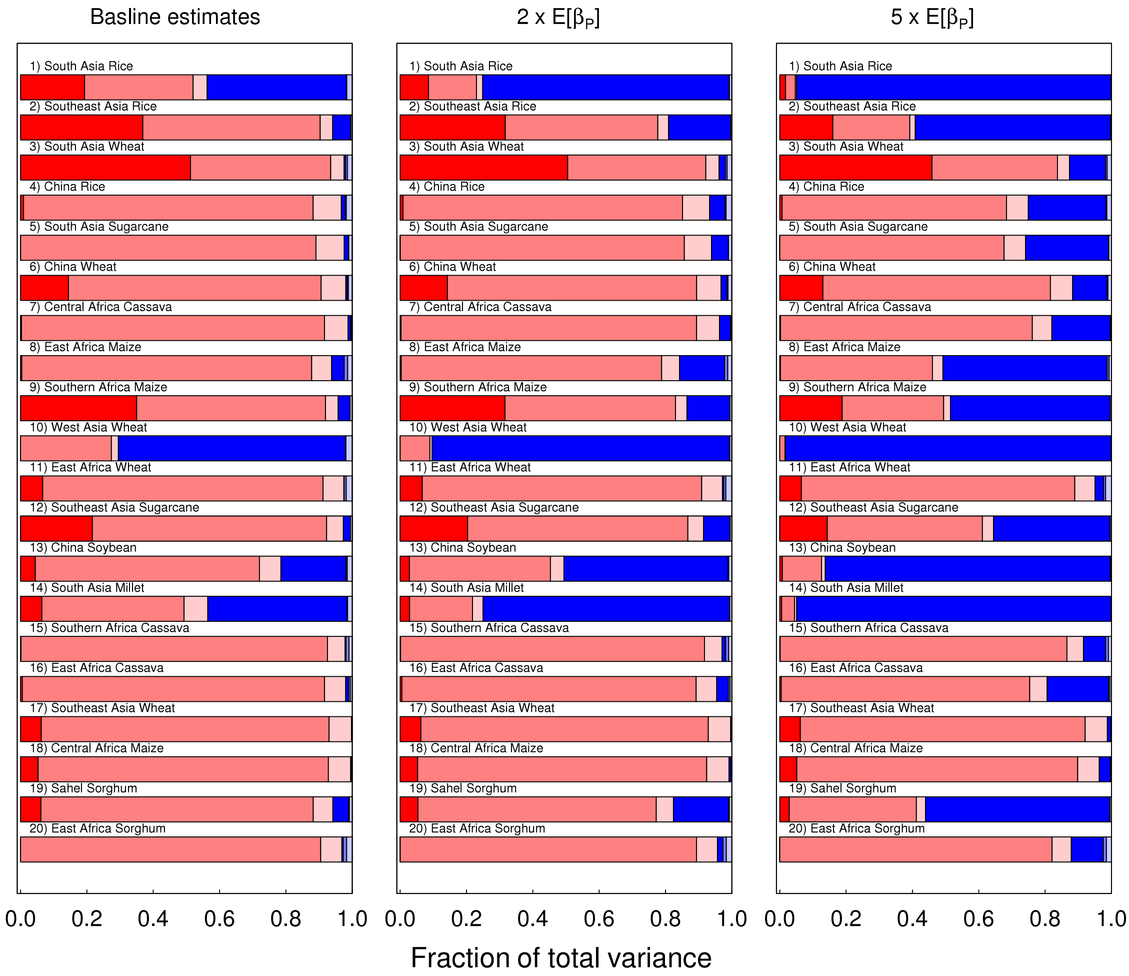

Figure 6. Sensitivity of results in figure 1(b) to an increase in the response of crops to rainfall (β_P) by two or five times. This is intended to show the potential effects of under-estimating the sensitivity of crop production to rainfall.

took 10 000 random combinations of the eight variables in equation (2), with the distributions defined in figure 3, and computed the fraction of total variance arising from temperature. In fully 92% of cases, temperature terms contributed more than half of total variance, and in 81% of cases more than three-fourths. Thus, the qualitative result that temperature related uncertainties drive most of overall impact uncertainty appears robust. As a final test, the results in figure 1(b) were re-generated after inflating the estimates of $E[\beta_P]$ in each crop–region combination by a factor of two and five (figure 6). Only if the importance of rainfall to crops (β_P) is roughly five times as large relative to β_T as we estimate here would terms related to rainfall contribute more than half of total uncertainties for most crops.

An important remaining question is whether the prospects for reducing uncertainty in ΔT or β_T are particularly good or bad. Roe and Baker [21] recently argued that uncertainty in global climate sensitivity to CO_2 is unlikely to be reduced substantially in the near term, because it results from climate system feedbacks that are hard to constrain with observations. Model projections of regional temperature change are determined largely (but not exclusively) by the model's global climate sensitivities [3], so that uncertainties in ΔT may be expected to persist for some time.

Prospects for reducing uncertainty for β_T are less clear. Two general approaches exist for estimating crop temperature sensitivity: detailed studies of processes through field and laboratory experiments, or statistical analyses of past temperature and crop production variations. The former require models to extrapolate results to broad scales relevant to impact assessments, although the temperature responses of these models are often poorly constrained by experiments and not well understood [22]. The latter approach, which underlies the models used in this study, is often hampered by variations in other yield controlling factors, the quality and spatial scale of available data, and by relatively small number of observations (∼40 years). Thus, some level of uncertainty is inevitable.

Of the 94 crop–region combinations considered in our study [14], the lowest uncertainty for β_T was found for South Asia wheat, with $\sigma(\beta_T) = 0.7\%$ per °C. To represent an optimistic scenario of relatively low uncertainty, we applied this value to all other crops, resulting in a reduction of total variance of impact projections by over half in most cases (figure 7). Constraining temperature sensitivities of all crops to the level of precision in South Asia wheat would thus substantially improve our ability to predict agricultural responses to climate change.

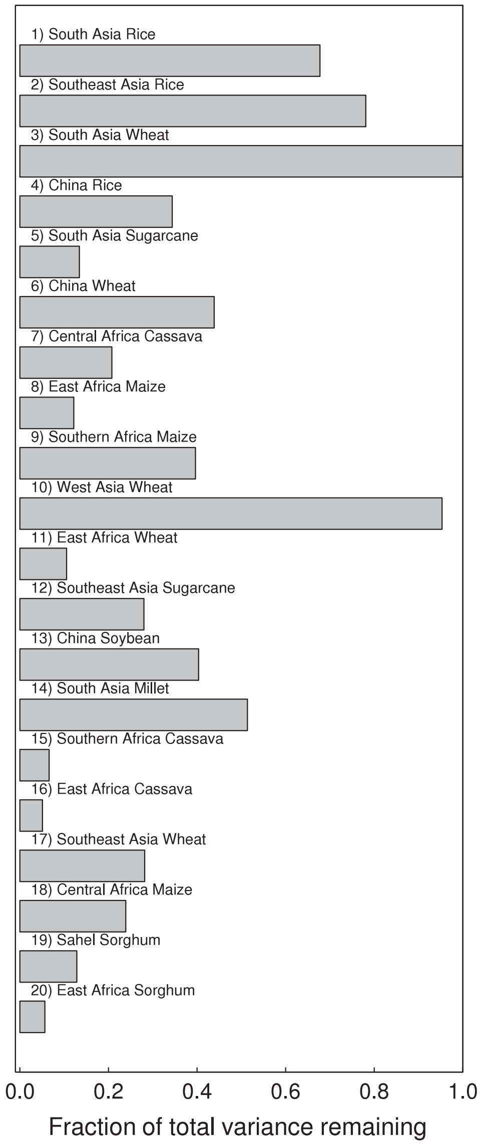

Figure 7. Fraction of total variance in climate change impact projections for 2030 remaining if the estimated value of $\sigma(\beta_T)$ is replaced by the lowest observed value across all crops (0.7% per °C), which represents an optimistic scenario of improved knowledge of crop temperature responses.

4. Conclusions

We find that, in general, uncertainties in average growing season temperature changes and the crop responses to these changes represent a greater source of uncertainty for future impacts than do associated changes in precipitation. This finding stems from the fact that future temperature changes will be far greater relative to year-to-year variability than changes in precipitation, even when considering the most extreme precipitation scenarios. These results do not imply that reduced uncertainties in rainfall projections would be useless, as projections for several critically important crops still derive much of their uncertainty from rainfall projections, such as rice in South Asia and wheat in West Asia. Moreover, the spatial scale of the datasets used here likely mute the importance of rainfall. Rather, it is our belief that the impact of temperature uncertainties, and in particular the uncertainties in crop response to temperature, should receive increased attention. The common approach of representing uncertainty only by examining output from different climate models risks a gross over-estimation of our current ability to predict agricultural responses to climate change. This conclusion is also supported by the few studies that have examined yield impacts with two separate process-based crop models. These studies have reported discrepancies between crop models as big or greater than those that result from different climate models, and attributed these discrepancies largely to the temperature coefficients in the models [10, 23]. Thus, the results presented here are unlikely to result from the exact specification of yield responses in equation (1), or to the fact that we relied on time series models rather than process-based models or cross-sectional data.

We considered here only uncertainties that relate to growing season average temperature and precipitation. Impacts of extreme events, pests and diseases, changes in solar radiation, and many other factors also add uncertainties to projections. In our opinion, all of these effects are likely to be captured by or secondary to those of average temperature change, but further work is needed to test this point. For example, the distribution of rainfall within growing seasons may change, with heavier but less frequent rainfall events in many regions [3], which could substantially change the relationship between growing season average precipitation and crop production. We also do not consider here adaptive management changes, which represent an additional but poorly known source of uncertainty in future impacts, even for the relatively short-term year of 2030 discussed here.

Despite these other uncertainties, the uncertain nature of crop responses to mean temperature change will remain an important factor for any risk assessment of climate change impacts that relies on accurate quantification of uncertainty. Crop model inter-comparison projects, similar to those used to assess climate model uncertainty [3], may be useful to this end in the short-run. Unlike climate sensitivity, however, the sensitivity of crops to warming can be experimentally tested. Warming trials for major crops across the range of environmental and management conditions in which they are most commonly grown may therefore be a particularly useful means of further prioritizing and focusing adaptation efforts.

Acknowledgments

We thank D Battisti, W Falcon, C Field, R Naylor, C Tebaldi for helpful discussions and two anonymous reviewers for comments on the manuscript. We acknowledge the modeling groups, the PCMDI and the WCRP's Working Group on Coupled Modeling (WGCM) for their roles in making available the WCRP CMIP3 multi-model dataset. Support of this dataset is provided by the Office of Science, US Department of Energy. This work was supported by the Rockefeller Foundation and by National Aeronautics and Space Administration Grant No. NNX08AV25G to DL issued through the New Investigator Program in Earth Science.

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