

# Biophysical and Economic Uncertainty in the Analysis of Poverty Impacts of Climate Change

*(Preliminary draft)*

Thomas Hertel ([hertel@purdue.edu](mailto:hertel@purdue.edu)), Purdue University  
David Lobell ([dlobell@stanford.edu](mailto:dlobell@stanford.edu)), Stanford University  
Monika Verma ([verma3@purdue.edu](mailto:verma3@purdue.edu)), Purdue University

## **Abstract**

This paper seeks to understand the main sources of uncertainty in assessing the impacts of climate change on agricultural output, international trade, and poverty. We incorporate biophysical uncertainty by sampling from a distribution of productivity shocks reflecting the impacts of climate on agricultural yields in 2030. These shocks, in turn, affect the global economy. The response of economic agents to climate change is the second source of uncertainty in our estimates. We find that, even though it is difficult to predict where in the world agricultural crops will be favorably affected by climate change, we find that the responses of output and exports can be far more robust. This is due to the fact that supply and demand decisions depend on relative prices, and relative prices depend on productivity changes *relative* to other crops in a given region, or relative to similar crops in other parts of the world. We also find that uncertainty in poverty impacts of climate change appears to be almost entirely driven by biophysical uncertainty. Further reducing this uncertainty will require improving climate models and the crop models used to interpret the impacts of likely future climate on crop productivity.

***Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's  
2011 AAEA & NAREA Joint Annual Meeting, Pittsburgh, Pennsylvania, July 24-26, 2011***

*Copyright 2011 by Hertel, Lobell and Verma. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.*

## **Introduction**

Globally, nearly 800 million people are chronically undernourished, and a large portion of these are children. In Sub-Saharan Africa, one of the regions expected to be most severely affected by climate change, the percentage of the population in poverty approaches 40 percent (Fischer, Shah, and van Velthuis, 2002). Given the large share of their budget is spent on food, these households are extremely vulnerable to commodity shortages. Indeed, the number of malnourished people at any point in time can change greatly in the face of commodity price spikes (Ivanic and Martin, 2008), in which supply has a role to play. This makes the poor especially vulnerable to climate change impacts on agriculture. Yet, while there has been considerable research undertaken on the agricultural impacts of climate change, and extensive research also on the determinants of poverty, there is a gap in research relating the two (Hertel and Rosch, 2010). This paper aims to contribute to filling this gap, by exploring the main sources of uncertainty in establishing the linkage between climate change, agricultural impacts of such change, and the ensuing poverty implications.

## **Sources of Biophysical and Economic Uncertainty**

There are many physical, biological, and economic processes that link climate change to poverty and food security – all of which introduce uncertainty into the resulting impact estimates. On the climate side, current science suggests that warming by 2030 is a relatively modest threat to food security. However, even on that time scale, it is plausible (5% probability) that average cereal prices could rise by 30% above baseline as a consequence of climate change, with significant production and poverty impacts (Hertel, Burke and Lobell, 2010). This possibility is further reinforced by recent statistical evidence that corn, soybeans and cotton yields exhibit non-linearities with respect to temperatures during the growing season, with the accumulation of temperatures above 30 degrees Celsius resulting in sharply declining yields (Schlenker and Roberts, 2006). On the other hand, there is some potential for near term climate change to benefit agricultural productivity due to warming in the higher latitudes, the potential for increased precipitation, and the benefits of CO<sub>2</sub> fertilization – particularly for rice, wheat and soybeans. In short, climate change and the agronomic impacts flowing from such change, remain a considerable source of uncertainty.

The economic response and adaptation to climate change is also a significant source of uncertainty. ‘Ricardian’ estimates of climate impacts on agriculture pioneered by Mendelsohn, Nordhaus and Shaw (1994) recognize that farmers will alter the mix of activities undertaken in the wake of climate change. These authors hypothesize that producers will choose to grow the crop or livestock type yielding the highest return on any given piece of land, and that, in long run equilibrium this should be reflected in underlying land values. However, they do not attempt to estimate the underlying parameters governing such adjustments. Rather, they simply assume that such adjustments will be reflected in observed returns to land. An alternative approach to

assessing adaptation possibilities in agriculture involves estimating the change in fundamental productivity of land in a given activity, thereupon using an economic model to predict how land will be reallocated, and variable inputs will be altered, in the wake of climate change. This is the approach taken by Nelson et al. (2010), Fischer (2009) and Hertel, Burke and Lobell (2010), to offer just a few examples. In the second approach, the economic parameters governing farmers' adaptation to climate change are explicit and include elasticities governing the responsiveness of land to changing returns in different uses, as well as the potential to vary input usage, including fertilizer, water and other factors, in response to changes in the biophysical and economic environment.

The poverty impacts of climate change will also depend on market responses to these agricultural impacts. In the case of an adverse climate shock, reduced supplies will result in higher prices for food, which will hurt net buyers. However, the magnitude of such price rises, and the severity with which they affect the poor, will depend critically on consumers' ability to substitute away from the higher priced products. In the case of the Indonesian financial crisis of the late 1990's, such consumer substitution was shown to greatly reduce the welfare impacts of higher rice prices (Friedman and Levinsohn, 2002). Aggregate demand response also serves as a vehicle to moderate the price rise following an adverse supply shock. And the same is true of supply response to scarcity. The latter will depend not only on yield and area response, but also on the flexibility of agriculture to adjust its workforce and capital stock in response to changing returns (Keeney and Hertel, 2008).

Finally, since climate change is a global phenomenon, with uneven impacts across geographic regions of the world, poverty impacts will also depend importantly on the degree to which price signals are transmitted across national borders. This is a topic which has generated considerable debate in the context of biofuels production. Villoria and Hertel (forthcoming) test the commonly maintained hypothesis of integrated world markets for coarse grains and reject it in favor of a differentiated products specification in which price transmission depends heavily on current trading partners and export competitors. Ahmed et al. (2010) examine the impacts of this geographic approach for trade in Tanzania; focusing on the potential for that country's producers to benefit from extreme climate events through increased exports. Of course, the transmission of price shocks across national borders also depends critically on trade policies. Martin and Anderson (2012) have shown that nations' attempts to shield their consumers from higher international prices in the wake of perceived scarcity in 2007/08 greatly exacerbated the global price rise during that period.

In summary, there is a plethora of different sources of economic uncertainty relevant to the assessment of poverty impacts of climate change. Previous authors have explored, in the context of other policy issues, the impact of such uncertainty on agricultural markets, land use and poverty, and we draw here on their insights and methodology. Keeney and Hertel (2008) seek to assess the global land use impacts of biofuel expansion in the US. From a global economic point of view, this issue is similar to the analysis of an adverse climate shock in the US. Both events

reduce the net supply of exports from the US to world markets. Those authors focus on the uncertainty associated with the economic responsiveness of yields, area under cultivation, labor and capital mobility and bilateral international trade patterns. Their systematic sensitivity analysis reveals that uncertainty in yield response is the dominant source of uncertainty in land cover change. However, when it comes to harvested area changes for specific crops, these varied sources of uncertainty are roughly of equal importance.

## **Methods**

Figure 1 outlines the methodology. It starts with projections of future Greenhouse Gas (GHG) concentrations in the atmosphere. These are uncertain and depend importantly on mitigation policies as well as future economic growth. Increased GHG concentrations are translated into changes in climate variables such as rainfall and temperature using climate models. There are nearly two dozen global climate models in use at present, each with different formulations and different predictions. This is an important source of biophysical uncertainty. This climate uncertainty is further compounded by uncertainty in the crop response to climate change, which, in turn feeds into our economic model which determines the resulting changes in agricultural supplies, prices, wages and poverty.

We follow Hertel, Burke and Lobell (2010) in using the Global Trade Analysis Project (GTAP) general equilibrium global trade model, database and poverty modules (Dimaranan, 2006; Hertel, 1997; Hertel et al., 2007) to explore the linkages between climate, agriculture and poverty. GTAP is a widely-used, comparative static, general equilibrium model which exhaustively tracks bilateral trade flows between all countries in the world, and explicitly models the consumption and production for all commodities of each national economy. Producers are assumed to maximize profits, while consumers maximize utility. Factor market clearing requires that supply equal demand for agricultural and non-agricultural skilled and unskilled labor and capital, natural resources and agricultural land, and adjustments in each of these markets in response to the climate change shocks determines the resulting wage and rental rate impacts. The model has recently been validated with respect to its performance in predicting the price impacts of exogenous supply side shocks, such as those that might result from global climate change (Valenzuela et al., 2007).

Following (Hertel et al., 2004), we identify 5 household groupings that earn >95% of their income from one source: agricultural self-employment, non-agricultural self-employment, rural wage labor, urban wage labor, or transfer payments (such as remittances or government aid). The remaining households not categorized in these 5 strata are grouped as rural diversified or urban diversified. The share of the poor in each of these socio-economic groups, coupled with data on earnings and consumption shares for households at the poverty line in each of the 7 strata, as well as poverty-income elasticities, permit us to predict changes in poverty headcount by stratum, given the price and earnings changes produced by the GTAP model.

Climate change is modeled via exogenous productivity “shocks” to selected agricultural crops. The size of these shocks is determined by biophysical studies and they do not reflect economic adaptation such as changing variable inputs and shifts in cropping patterns in response to climate change. In future versions of the paper we plan to base these productivity shocks on formal statistical analysis, which will permit us to associate explicit probability distributions with each crop/region combination. However, in the current version of the paper we draw on the probability distributions associated with the earlier paper by Hertel, Lobell and Burke (2010). Those authors synthesized productivity shocks based on previous studies in the literature, generating a “most likely” or “central-case” estimate for each region/commodity pair in the model, along with an estimate of “low-productivity” and “high-productivity” outcomes (Figure 2 illustrates these shocks for maize). The low productivity scenario depicts a world with rapid temperature change, high sensitivity of crops to warming, and a CO<sub>2</sub> fertilization effect at the lower end of published estimates. The high productivity scenario represents a world with relatively slow warming, low sensitivity of crops to climate change, and high CO<sub>2</sub> fertilization. These estimates were intended to bracket a range of plausible outcomes ranging from the 5<sup>th</sup> and 95<sup>th</sup> percentile values in a distribution of potential yield impacts. By using these points/probabilities, we are able to construct, for purposes of this study, a full, triangular distribution of productivity shocks for use in our systematic sensitivity analysis of the impacts of climate change on global agricultural production.

With these climate shocks, it remains to characterize the uncertainty associated with the economic response to climate change. The responsiveness of the various components of supply and demand is typically characterized in terms of unit-free elasticities describing the percentage change in economically optimal quantities in response to a change in relative prices. In this study, we focus on the elasticities which have been deemed central to determining the poverty impacts of climate change including: the elasticity of yields with respect to commodity price<sup>1</sup>, the elasticity of land supply, the elasticity of labor and capital supply to agriculture, the elasticity of consumer demand for food, and the elasticity of substitution amongst agricultural products in international trade. Distributions for each of these parameters are established based on prior econometric work, as well as theoretical restrictions and previous studies.

With the underlying productivity distributions for the climate shocks and distribution of economic responses to the induced price changes, we are able to conduct an exhaustive Systematic Sensitivity Analysis (SSA) to infer the likely poverty consequences. SSA uses the Gaussian Quadrature (GQ) approach to estimate means and standard deviations of model results. The GQ approach as described DeVuyst and Preckel (1997) and Arndt (1996) and as implemented in GEMPACK (Pearson and Arndt, 2000) is much more efficient than Monte Carlo and is therefore appropriate for large models, where the solution time makes it prohibitive to undertake thousands of simulations. Furthermore, recent improvements in the GQ algorithm

---

<sup>1</sup> In the GTAP model, this is governed by the elasticity of substitution between land and non-land inputs, which is the parameter to be varied.

(Preckel et al., 2011) can be used to ensure that sampling also includes extreme points from the underlying probability distributions.

A final point relates to the state of the global economy to which we are applying the climate shocks. Rather than projecting the entire world economy forward to the year 2030, we adopt the much simpler approach of imposing the climate change shocks on our base year economy (2001). This is not because intervening changes in the global economy will be unimportant. On the contrary, as will be discussed in our concluding section, the global composition of poverty in 2030 will be critical to these outcomes. However, little is known about how global poverty will evolve over the coming decades. Rather than confusing the reader by adding another source of uncertainty to the analysis, we prefer to simply overlay the climate shocks on a global economy/poverty distribution that has been recently observed.

## Results

We first undertake the SSA with respect to biophysical uncertainty alone. The results are summarized in the top panel of Table 1. The table reports percentage of observations of productivity, output and exports for four major crop categories which are statistically significant. In this case, the productivity shocks represent an *input* to the simulation, whereas the supply and export results are *simulation outputs*. What is immediately apparent is that, while the majority of the inputs are uncertain, i.e., we cannot say whether productivity of a given crop in a given region will rise or fall in the wake of 2030 climate change, the resulting consequences for important economic variables, including crop output and bilateral exports, are rather certain! This is surprising, given that the latter are outcomes, based on the former configuration of shocks. Of course, we have not yet introduced uncertainty in economic responses.

The second panel in Table 1 combines uncertainty in the underlying biophysical shocks stemming from climate change, with uncertainty in the economic response to the resulting scarcity/surplus conditions created in commodity and factor markets. Not surprisingly, the uncertainty associated with productivity changes by crop and region is unchanged, as these are inputs to the analysis. Furthermore, the economic uncertainty generally reduces the number of supply and export observations that are statistically significant. However, even when uncertainty in the economic system is factored into the SSA, supplies for each commodity are globally still more certain than the underlying productivity shocks for all four crop categories, and, with the exception of coarse grains, exports are substantially more certain than both output and productivity changes.

Figure 3 provides a visual display of this puzzle. In the lower left hand panel, productivity shocks are displayed as points in a scatter plot, wherein the horizontal axis denotes the percentage deviation from baseline owing to climate change, and the vertical axis reports the t-statistics associated with each outcome. Thus the points in the lower left hand quadrant correspond to region/commodity outcomes in which climate change reduces productivity of the

crop in question, but the change is deemed insignificant. There are many such outcomes. There are also quite a few outcomes in which climate change appears to boost productivity, relative to baseline, but the associated t-statistic is less than two, suggesting insignificance. There are fewer observations above the horizontal axis which represents  $t = 2.0$ . The negative and significant regional productivity shocks correspond to maize, while most of the positive and significant productivity changes refer to oilseeds. Finally, as expected, the scatterplot is shaped like a funnel, with greater spread at the top, as one would expect i.e. larger positive and negative shocks are more likely to be significant.

The two upper panels in Figure 3 report the results for changes in output and exports in the face of combined biophysical and economic uncertainty. The first thing to note is that the bulk of the observations now lie above the significant line ( $t = 2.0$ ). There are also many more diverse points in these figures, as the biophysical estimates are undertaken at larger geographic scale than are the economic estimates. (E.g., there may be just one estimate for productivity changes due to climate in Southern Africa, but there are several different countries in the economic model, each with a different economic impact due to the different economic structure of their economies.) Also, while oilseeds productivity shocks were disproportionately positive and coarse-grains disproportionately negative, this does not translate into such a clear predominance in the sign of the associated economic variables.

Resolving these apparent puzzles requires us to return to economic theory, as reflected in the underlying GTAP model.

Let's start with the output. Output of a crop in a given region is affected by climate change (through yields); *ceteris paribus* an increase in yields will increase the output, irrespective of the magnitude of yield changes for other crops in the region. We call this the direct affect of climate change on crop output. However not all the output change in the model can be explained though this simple relation, there are cases where, despite negative yield shocks, output witnesses an increase. This can be explained by the increased supply of land to the concerned crop.

This land supply change is an indirect effect of climate change on output, as the differential yield impacts lead to land reallocation between the affected crops. To understand this effect, it is useful to consider land allocation, given as follows:

$$qoes_{ijr} = \sigma_{Lir} \cdot [pmes_{ijr} - pm_{ir}] \quad (1)$$

where  $qoes_{ijr}$  describes the percentage change in optimal supply of land type  $i$  to crop  $j$  in region  $r$  as function of the percentage change in the relative return to cropland devoted to cultivation of crop  $j$  in that particular Agro-Ecological Zone,  $pmes_{ijr}$  compared to the average for all cropping activities in the AEZ. To a linear approximation, the percentage change in this ratio is just the difference in the two percentage changes, and this difference is pre-multiplied by

the elasticity of land mobility in that AEZ/region,  $\sigma_{Lir}$ . The latter is based on econometric analysis of the historical supply response of land to specific crops.

The key thing to note about equation (1) is that land supply response in a given region is a function, not of absolute returns, but rather of *relative* returns to different cropping activities. One should therefore not be surprised by a one to one correspondence in the rankings of net returns to land under a crop and its supply to that crop. Following the same chain of logic, the relative returns to land in a particular crop depend on the relative factor demand for land in that crop, the higher the demand of land to produce rice the more profitable it becomes to move land from other crops into rice. The relative land demand across crops in turn, is affected by the relative yield changes across the crops; a positive yield shock reduces the derived demand for all inputs, *ceteris paribus*. This has important implications when it comes to determining the crop supply impacts of climate change. If one crop is systematically more harshly affected by climate change than another, then, regardless of whether the biophysical productivity effect is positive or negative, the sign of the resulting output change is will be clear cut. Output will rise for the relatively more favored crop. While these are not the only explanatory factors behind land use changes but they are important, and dictate the direction of change in the majority of our simulation results.

The second relationship of interest is one which reflects the competitiveness of similar crops supplied by different regions, and hence determines trade patterns. Change in volume of exports is given as weighted sum of exports to the destinations

$$qxw_{ir} = \sum_s s_{irs} \cdot qxs_{irs} \quad (2)$$

where  $qxs_{irs} = qim_{is} - \sigma_{Mi} \cdot [pms_{irs} - pim_{is}]$

This states that the percentage change in the demand for imports of commodity  $i$  exported from region  $r$  to region  $s$  depends on the percentage change in aggregate imports of  $i$  into  $s$ , as well as the relative price of supplies from  $r$ , compared to the average price from all sources exported to region  $s$ ,  $pim_{is}$ . The responsiveness of relative trade to relative price changes hinges on the elasticity of substitution amongst imports,  $\sigma_{Mi}$ . This is the equation that determines the change in exports of agricultural commodities reported in Figure 3 and Table 1, and it clearly shows that what matters is not the absolute price change, but rather the relative change in supply prices for, e.g., rice, from different producing regions. The regions with a favorable supply price for a crop, relative to its world average, will tend to increase exports of the crop. Of course, these relative supply prices will be affected by relative yield shocks, so what matters is whether climate change favors one region (e.g., Canada) relative to another region (e.g., South Africa) in a systematic fashion for the crop. If this relative shock is certain for a given crop, then, even if the sign of the climate impact on yields in the two regions is uncertain, the sign of the resulting trade flow will be significant.

Thus far, we have only discussed the impact on crop output and exports. However, what we are most interested in are the poverty impacts of climate change.

Figure 4 reports the national poverty impacts for our 15 sample countries, in thousands of people, along with 95% confidence intervals. These results are reported both for biophysical uncertainty alone (red bars) and for biophysical uncertainty when combined with economic response uncertainty. The first thing to note is that the national poverty impacts are uncertain in virtually every region of the world which we have been able to include in our analysis. The 95% confidence intervals for poverty headcounts are wide indeed and vary from a minimum of 800 hundred for Vietnam to a maximum of 3104 thousand for Indonesia.

The second important result is that the economic response uncertainty has little effect on the poverty uncertainty (the red and the green lines have almost the same length). In effect, if there is an adverse impact in a given region of the world, then its people are likely to suffer, regardless of which crops they grow and whether they sell these crops at home or abroad. Therefore, if we wish to narrow the degree of uncertainty about the poverty impacts of climate change, we must focus on narrowing the biophysical uncertainty.

Figure 5 breaks out the poverty impacts by socio-economic group for three different countries: Peru, Uganda and Vietnam. Here, we see that different groups within each country are differentially affected by climate change. In these three regions, poverty rises in the agricultural groups, but while it's the worst affected group in Peru, the corresponding groups in Vietnam and Uganda are the rural diversified, its true for both the mean and the standard deviation of the poverty headcount estimate.

## References

- Ahmed S.A., T.W. Hertel and W. Martin. 2011. Climate Volatility and Trade Policy in Tanzania. Paper presented at the 13th Annual Conference on Global Economic Analysis, Penang, Malaysia
- Arndt, C. 1996. "An Introduction to Systematic Sensitivity Analysis Via Gaussian Quadrature." GTAP Technical Paper No. 2. Available at: [www.gtap.org](http://www.gtap.org).
- DeVuyst, E.A., and P.V. Preckel, 1997. "Sensitivity Analysis Revisited: A Quadrature Based Approach." *Journal of Policy Modeling*. 19(2), 175-85.
- Dimaranan, Betina V., Editor (2006). *Global Trade, Assistance, and Production: The GTAP 6 Data Base*, Center for Global Trade Analysis, Purdue University.
- Fischer G., M. Shah, and H. van Velthuizen. 2002. *Climate Change and Agricultural Vulnerability*. A special report, prepared by the International Institute for Applied Systems Analysis; contribution to the World Summit on Sustainable Development, Johannesburg 2002.
- Fischer, Günther. 2009. How do climate change and bioenergy alter the long-term outlook for food, agriculture and resource availability? In *Session 2: The resource base to 2050: Will there be enough land, water and genetic potential to meet future food and biofuel demands?* Rome, Italy, June 24.
- Friedman, J. and J. Levinsohn, 2002, The Distributional Impacts of Indonesia's Financial Crisis on Household Welfare: A 'Rapid Response' Methodology, *World Bank Economic Review* 16(3), 397-423.
- Hertel T.W., M.B. Burke and D.B. Lobell. 2010. The poverty implications of climate-induced crop yield changes by 2030. *Global Environmental Change*, Volume 20, Issue 4, October 2010, p. 577-585.
- Hertel Thomas W., M. Ivanic, P. V. Preckel, and J. A. L. Cranfield, 2004. "The Earnings Effects of Multilateral Trade Liberalization: Implications for Poverty", *The World Bank Economic Review*, Vol. 18(2), pp. 205-236.
- Hertel, T. W. (ed) (1997) *Global Trade Analysis: Models and Applications*. Cambridge University Press.
- Hertel, T.W., Keeney, R., Winters, L.A., 2007. Distributional effects of WTO agricultural reforms in rich and poor countries. *Economic Policy* 22 (50), 289–337.
- Hertel, T. W., & Rosch, S. (2010). Climate Change, Agriculture and Poverty. *Applied Economic Perspectives and Policy*, 32(3), 355-385.

Ivanic, Maros & Martin, Will, 2008. "Implications of higher global food prices for poverty in low-income countries," *Agricultural Economics*, Volume 39, Supplement, Date: November 2008, Pages: 405-416.

Keeney, R., and T. W. Hertel. 2008. "The Indirect Land Use Impacts of U.S. Biofuel Policies: The Importance of Acreage, Yield, and Bilateral Trade Responses." GTAP Working Paper No. 52, Center for Global Trade Analysis, Purdue University, West Lafayette, IN.

Martin, W., and K. Anderson. 2012. "Export Restrictions and Price Insulation During Commodity Price Booms." *American Journal of Agricultural Economics* 94 (1), (forthcoming).

Mendelsohn R., W. Nordhaus and D. Shaw. 1994. The impact of global warming on agriculture: a Ricardian analysis. *The American Economic Review*, 84(4), p.753–771.

Nelson, Gerald C., Mark W. Rosegrant, Jawoo Koo, Richard Robertson, Timothy Sulser, Tingju Zhu, Claudia Ringler, et al. 2010. *The Costs of Agricultural Adaptation to Climate Change*. International Food Policy Research Institute (IFPRI).

Pearson, K., and C. Arndt, 2000. Implementing Systematic Sensitivity Analysis Using GEMPACK. GTAP Technical Paper No. 3. Internet site: [www.gtap.org](http://www.gtap.org)

Preckel, P.V., M. Verma, T.W. Hertel and W. Martin. 2011. Systematic Sensitivity Analysis for GTAP – Where We've Been and Where We're Going. Selected paper for 14th Annual Conference on Global Economic Analysis, 16-18 June 2011, Venice, Italy.

Schlenker W. and M.J. Roberts. 2006. Nonlinear Effects of Weather on Corn Yields, *Review of Agricultural Economics*, 28(3), p. 391-398.

Valenzuela E., Hertel T. W., Keeney R. and Reimer J., 2007. Assessing Global Computable General Equilibrium Model Validity Using Agricultural Price Volatility, *American Journal of Agricultural Economics*; May 2007, Vol. 89 Issue 2, p383-397.

Villoria N. and T.W. Hertel (forthcoming). Geography Matters: International Trade Patterns and the Indirect Land Use Effects of Biofuels. *American Journal of Agricultural Economics*,

# METHODOLOGY

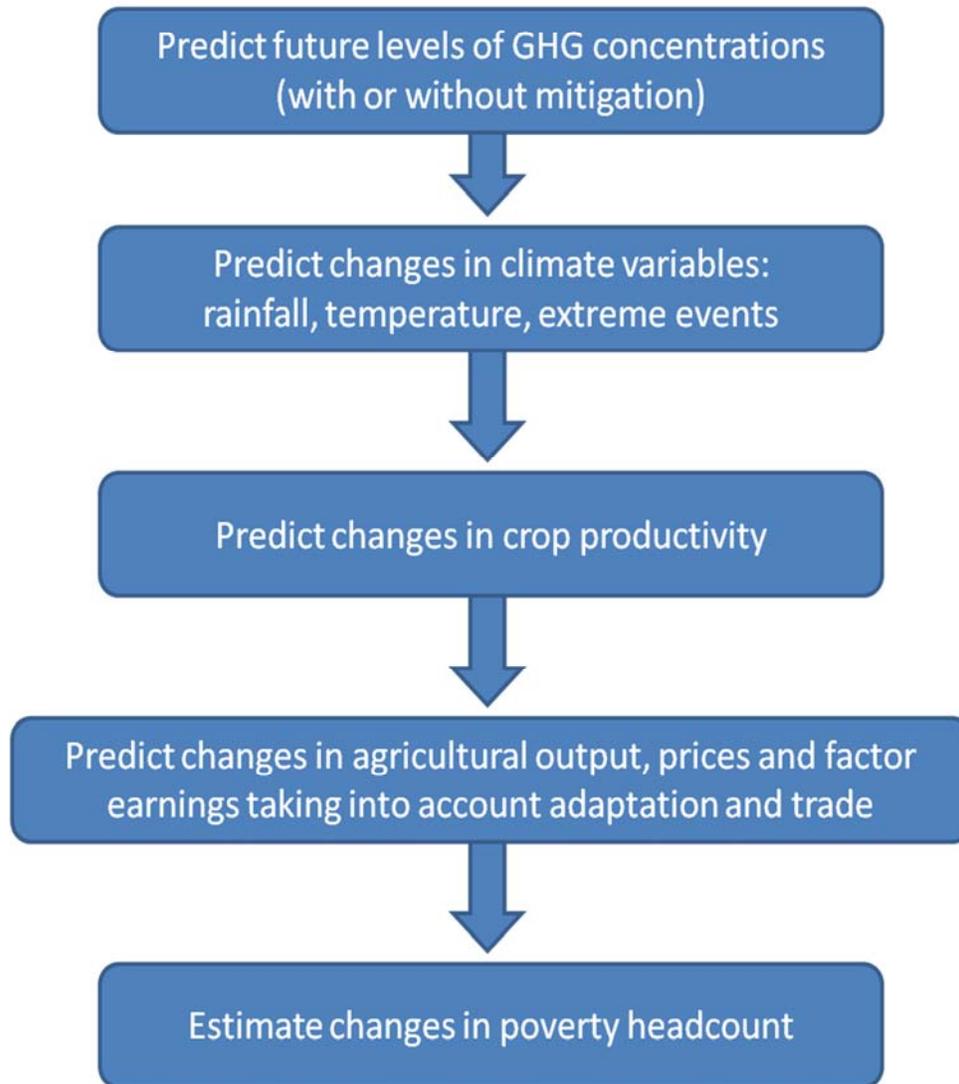


Figure 1. Methodology for assessing the poverty impacts of climate change through agriculture

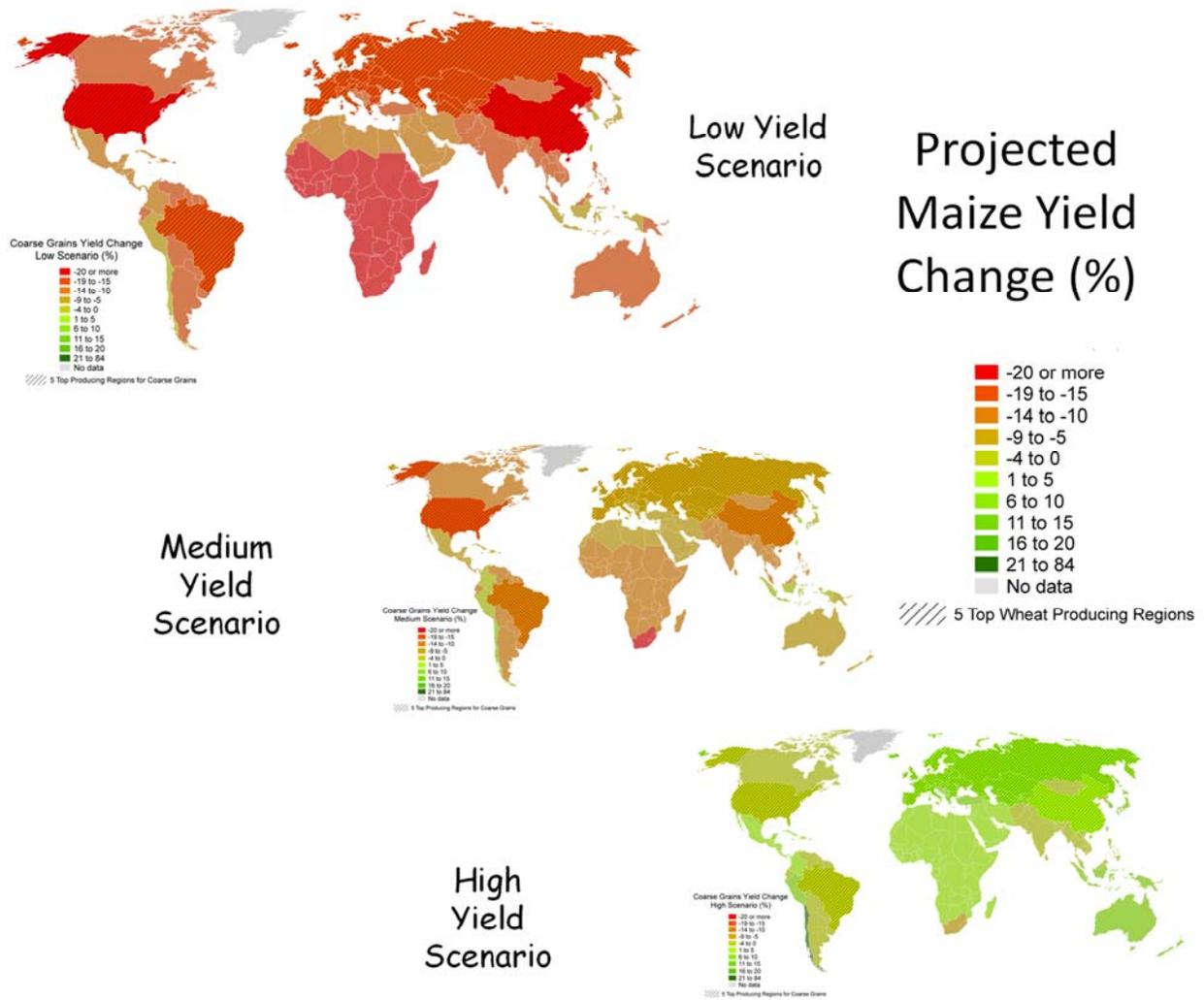


Figure 2. Impact of climate change in 2030 on maize yields: low (fifth percentile of the productivity distribution) medium (expected value) and high (ninety-fifth percentile) productivity outcomes, expressed as percentage change from baseline in the absence of adaptation

### RESULTS: YIELD, PRODUCTION AND TRADE UNCERTAINTY

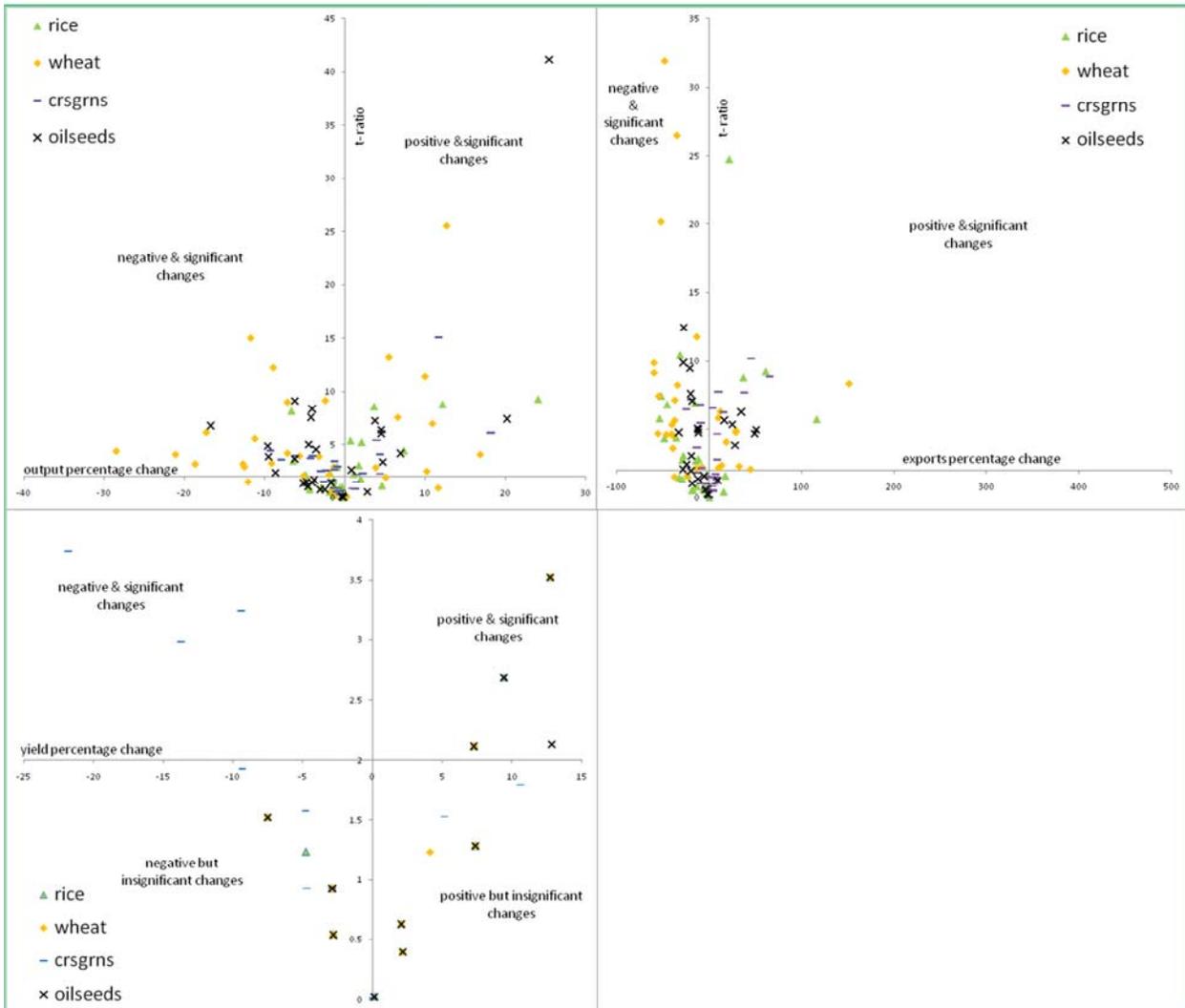


Figure 3. Productivity (yield without adaptation), supply and trade uncertainty for rice, wheat, coarse grains and oilseeds, by region in the global model. X-axis charts the percentage change in each variable. Y-axis charts the absolute value of the t-statistics associated with each variable: entries above 2.0 are deemed ‘statistically significant’.

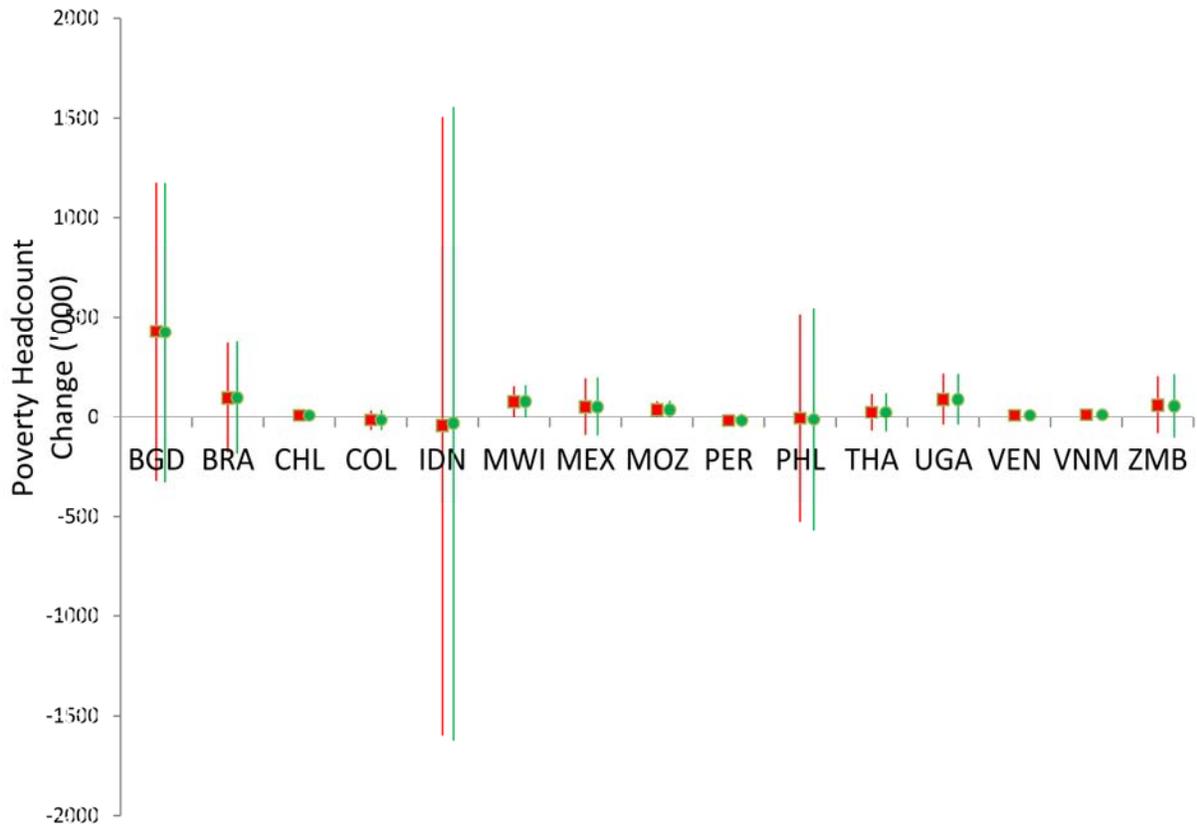


Figure 4. National poverty headcount impacts of climate change in the presence of biophysical (red) and both biophysical and economic uncertainty (green): thousands of people. Expected values and 95% confidence intervals.

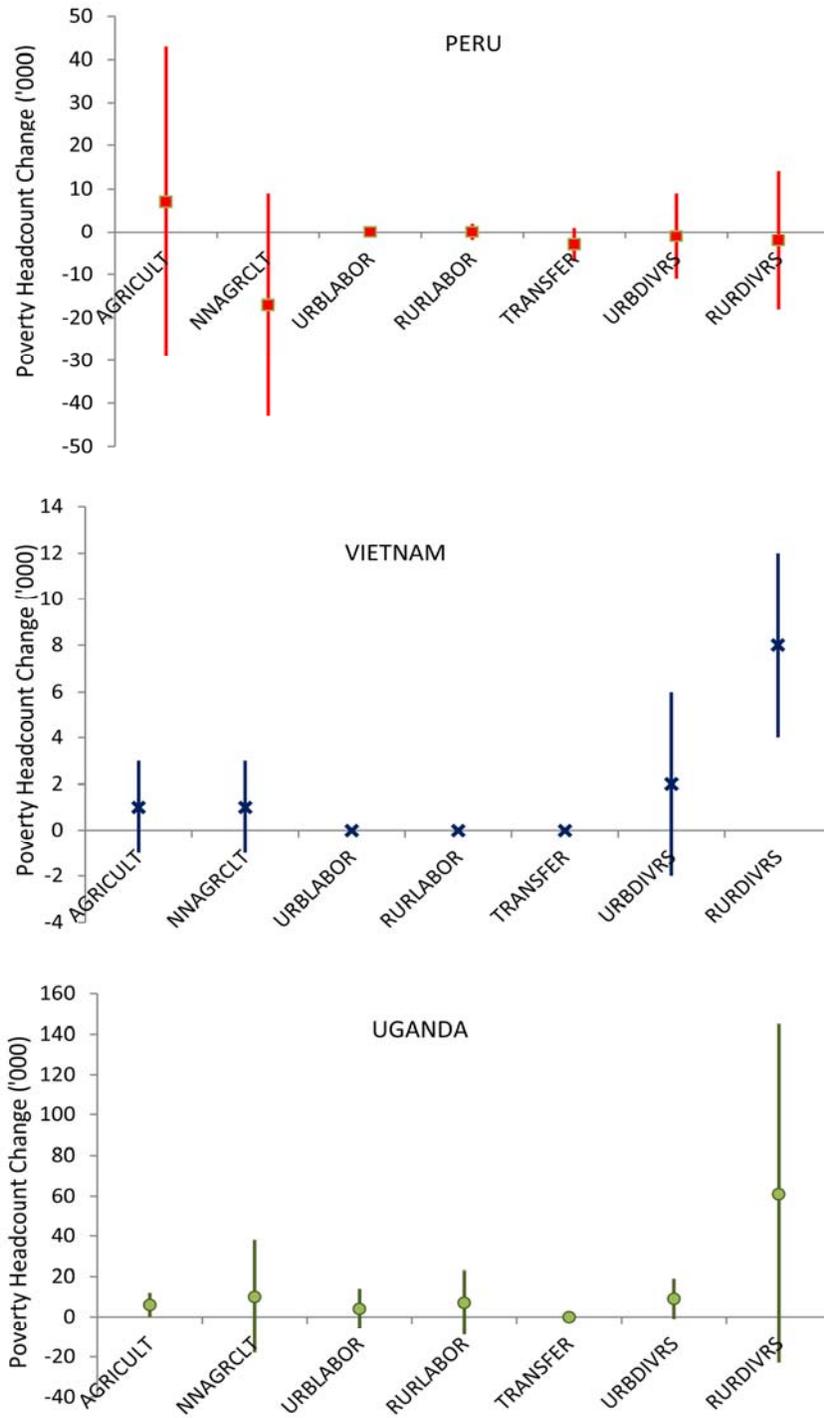


Figure 5. Stratum poverty headcount impacts of climate change in the presence of both biophysical uncertainty: thousands of people by seven socio-economic groups. Expected values and 95% confidence intervals.

<u>Biophysical Uncertainty</u>				
		Variable		
		Yield*	Output	Exports
Crop	Rice	15%	44%	62%
	Wheat	12%	82%	94%
	Crsgrans	41%	65%	53%
	Oilseeds	18%	68%	76%
<u>Biophysical and Economic Response Uncertainty</u>				
		Variable		
		Yield*	Output	Exports
Crop	Rice	15%	41%	47%
	Wheat	12%	68%	79%
	Crsgrans	41%	47%	38%
	Oilseeds	18%	68%	76%

Numbers reflect the proportion of sample for which the results are significant

\* Yield numbers don't change as they reflect climate uncertainty not dependent on economic response

Table 1. Summary of the uncertainty results for productivity, supplies and exports, by commodity, in the face of biophysical uncertainty alone, and both biophysical and economic uncertainty. Entries report the percentage of regional results for each variable that are statistically significant.