CHAPTER

3

Are Climate Change Adaptation and Mitigation Options Eco-Efficient?

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Contents

Abstract

This chapter provides an overview of predicted global climate change, placing special emphasis on the implications for agriculture. The power of modelling for understanding both impacts on productivity and adaptation options is demonstrated. The models on agricultural production for 50 crops predict significant impacts, with both winners and losers. The resultant need for systems reconstruction in highly vulnerable areas demonstrates a possible entry point for eco-efficient agriculture, in parallel with demands for adaptation measures that are climate smart and deliver on mitigation co-benefits. The chapter then focuses on Colombia and provides an end-to-end analysis of projected climatic changes for 2050, the impacts this may have on agriculture, and mitigation and adaptation options in the country's rice sector. Priority options include managing the methane emissions of flooded rice, eliminating crop residue burning, irrigation, genetic modification for heat tolerance, and increasing efficiency of nitrogen fertilizer application. The relevance of eco-efficient agriculture in adapting to and mitigating climate change is discussed, with special emphasis on synergies between eco-efficiency and climate change adaptation or mitigation.

Introduction

Climate change is widely considered one of the major drivers of societal change in the coming century, and agriculture has been identified as particularly exposed and vulnerable to its impacts (Lobell et al., 2008; Roudier et al., 2011; Thornton et al., 2011). In addition to crop losses from the increased incidence of natural disasters (floods, droughts, fires, etc.) (Sivakumar et al., 2005; Tao

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et al., 2009), agricultural systems will have to cope with changing rainfall regimes, geographical shifts in the occurrence of pests and diseases (Garrett et al., 2012; Jarvis et al., 2012), shorter growing seasons (Jones and Thornton, 2009), temperature stress (Challinor et al., 2007) and loss of climatic suitability (Jarvis et al., 2012). Global climate models[4] (GCMs) predict that while climatic variability is certain to produce both winners and losers, the losses will far outweigh the gains in many cases. The tropics, in particular, are expected to experience crop yield decreases in the order of 10–30% (Moorhead, 2009). Likewise, South Asia might well be too heat stressed to grow wheat by 2050 (Ortiz et al., 2008; Lobell et al., 2012). Both of these regions depend heavily on agriculture for rural livelihoods, making them especially susceptible to climate-change-induced pressures.

Agriculture's position in the climate change equation is perhaps unique; it is simultaneously a highly vulnerable sector as the numbers above indicate, a highly culpable sector with regard to its significant contribution to anthropogenic emissions (Key and Tallard, 2012), and also a sector with enormous potential for mitigating anthropogenic climate change (Hutchinson et al., 2007; Tubiello and Fischer, 2007). Indeed, agriculture produces a disproportionate share of emissions of the high-impact gases methane (CH_4) (47% of global total) and nitrous oxide (58% of global total) (Pye-Smith, 2011). It is responsible for 30% of all greenhouse gas emissions when taking into account land use change and deforestation for agricultural expansion, fuel, fiber, and food (IPCC 2007). On the other hand, carbon sequestration in agricultural soils could potentially offset 5–15% of global fossil fuel emissions (Lal, 2004), not to mention the mitigation power of deforestation reduction and fertilizer and irrigation optimization through sustainable intensification practices.

These considerations make climate-smart agriculture a critical topic for discussion and rapid action. Changing conditions require transformations in agricultural systems towards higher productivity, but on a lower-emissions trajectory (FAO, 2010a). Climate-smart agriculture aims to achieve food security for a world of 9 billion people and successful adaptation to an increasingly variable climate, while reducing emissions and sequestering carbon. It includes practices such as agroforestry, mulching, water management, intercropping, and silvopastoralism, as well as technologies for climate risk management, such as more accurate weather forecasts and the development of improved food crop varieties (Cooper et al., 2012; Smith et al., 2011; The World Bank, 2011). Specific definitions for climate-smart agriculture can vary widely depending on the source. For the purposes of this chapter we will use the following definition for climate-smart agriculture: an agricultural system employing practices which (a) contribute to farmer adaptation to climate change by bolstering the security of food systems, or (b) help to mitigate climate change by sequestering or preventing the release of carbon emissions, while (c) ideally increasing agricultural productivity.

Although climate-smart agricultural practices have been shown to be effective in matters of adaptation and mitigation, there remains the question of whether a climate-smart practice is necessarily an eco-efficient practice. When applied to agriculture, eco-efficiency describes a system that produces the most possible output with the least possible input, harmonizing economic, social, and environmental needs (see Mateo and Ortiz, Chapter 1 of this publication). But to what extent do eco-efficient practices overlap with climate-smart practices? Although climate-smart farming practices may be able to reduce emissions from agriculture, do they also constitute a system that uses resources effectively and efficiently for maximum yields?

This chapter shows how climate and crop models can be used to anticipate future scenarios for agricultural development and support decision making for priority adaptation and mitigation interventions. Future projections are presented, which are then used to evaluate impacts on agricultural production and systems. The chapter

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[4] Global climate models, the term that we use here, are also called "global circulation models" and "general circulation models" by other authors.

then presents a case study of Colombia, where likely climate changes are quantified, impacts on agricultural systems are assessed, and the efficacy of different adaptation and mitigation options for the country are outlined. This example is then used to discuss whether climate change presents a challenge or an opportunity for eco-efficient agriculture, looking at the impacts and potential responses in a broader political economy. Using the example, we address the following question: are the high-priority adaptation and mitigation options identified for Colombia necessarily eco-efficient as well?

Aspects of global climate change relevant to agriculture

Predicted changes in the climate system

While GCMs are all based on the same underlying principles, they vary in their implementation. We rely on the comprehensive collection of GCM climate change data and statistics of the Intergovernmental Panel on Climate Change (IPCC) for the scenarios presented here.

The IPCC used 24 GCMs in its Fourth Assessment Report (AR4) (IPCC, 2007) to show changes in climatic variables at various times in the future. The predictions depend on which of the various scenarios of economic and environmental development is assumed to occur, analyzed in detail in the IPCC's Special Report on Emissions Scenarios (SRES) (IPCC, 2000). Overall, annual mean temperatures are predicted to increase by 1–3° C by 2050 (depending on the SRES scenario), with mid- to high latitudes likely to warm at higher rates than the tropics. Changes in rainfall are varied and complex, ranging from -10 to +20% (again depending on the SRES scenario), with very high likelihood of increases along the Pacific coast of South America and in Eastern Africa, and decreases over South Asia (IPCC, 2007). More specifically, under the SRES A2 scenario ("business as usual"), global mean temperatures are predicted to rise by 1.6–8.4 °C by 2050, with winter temperatures and northern latitudes increasing most, while global average rainfall is predicted to increase as much as 1.9% by 2020 and 22.8% by 2050 (IPCC, 2007).

Again under the SRES A2 scenario, the Mediterranean area of North Africa extending towards the Sahara is predicted to be drier throughout the year. Changes in rainfall in Asia are spatially variable, while in the Middle East, predictions show a decrease in overall rainfall [although with low certainty (IPCC, 2007)]. Changes in rainfall in the Amazon are highly uncertain, ranging from -10 to +15% by 2050.

All of these changes are expected to have profound implications for world agriculture, but the impact will depend on: the crop grown, farmer adaptability to climate change, type and severity of the expected change, and the current system vulnerability. Coping with these changes requires reliable predictions of future climate, coupled with reliable impact models and knowledge of adaptation options that can be implemented at the individual farm level (Jarvis et al., 2011; Thornton et al., 2011).

Uncertainties in climate modelling

We cannot measure the response of the climate to natural or anthropogenic forcings in absolute terms, but we can represent it in GCMs. GCMs themselves, however, are based on imperfect approximations that cause inaccuracies and uncertainties. Inaccuracies occur when we do not reproduce observed climate patterns at the scales that they appear (i.e., predicted climates differ from observations). In contrast, uncertainties reflect the variability (i.e., spread) of GCM predictions and can arise from:

- Disagreement on the future socio-economic behavior of the world's nations, leading to disagreement over which SRES scenarios to use
- Lack of understanding of the response of the climate system to anthropogenic forcing
- Inability to understand properly, and hence model, the different forcings in the climate system, which are then parameterized differently in the GCMs
- Disagreement over GCMs' initial conditions (i.e., the fact that climate change experiments are initialized arbitrarily on the basis of a quasi-equilibrium control run) (Challinor et al., 2009).

Often the conditions necessary to initialize GCMs in climate change experiments must be selected randomly (Gleckler et al., 2008; Taylor et al., 2012), which contributes to model spread. Uncertainties, therefore, are a range of predictions for any future time giving us a plausible range under which the impact of potential adaptation- or mitigation-oriented decisions can be analyzed (Moss et al., 2010; Webster et al., 2012). Quantifying these uncertainties is critical to understanding the future changes in climate and how agricultural systems will respond to them (Challinor et al., 2009; Moss et al., 2010).

Given enough observed data, we can assess the predictive skill for any climatic variable prediction by the GCMs, but a variable that performs well in one instance (i.e., present-day climate) may not perform well in others (i.e., future scenarios) (Challinor and Wheeler, 2008). In addition, the uncertainty determined for one variable does not necessarily represent the uncertainty of all the others. That is, one variable's estimate of "high uncertainty" does not signify that the projection is highly uncertain in absolute terms. Quantification of uncertainty is critical for decisions regarding adaptation of agricultural systems to climate change (Smith and Stern, 2011; Smith et al., 2011). These decisions directly impact farmers' livelihoods and therefore need comprehensive analysis of current vulnerabilities and future uncertainties to avoid the risk of making faulty recommendations (Jarvis et al., 2011).

Decision making under uncertainty

Despite the inherent uncertainties in climate change projections, there can be no excuse for inaction on the policy front. On the contrary, decisions on adaptation strategies should be anticipatory, putting into place as much effective policy and infrastructure as possible in the near term to avoid possibly irreversible repercussions. Moreover, anticipatory adaptation has the additional benefit of reducing the potential costs that may result from maladaptation, particularly for decisions regarding long-lived and costly infrastructure or sector-level planning (Ranger et al., 2010).

Climate change adaptation is by no means without risk. Decision makers may fail to appreciate the magnitude of a climate-related risk and not deliver a crucial adaptation, or there is the possibility of overestimation of risk and thus "over-adaptation" and waste of resources (Willows and Connell, 2003). Although we cannot predict with complete certainty how the climate will be in the future, it is possible to take steps to buffer negative effects with minimum levels of risk. That is to say, adaptation does not necessarily require a perfectly accurate prediction. A framework developed by Willows and Connell (2003) emphasizes the necessity of keeping open or increasing the options that could allow adaptation measures to be implemented in the future, when the situation may be less uncertain.

According to Willows and Connell (2003), risk assessments should aim to identify "no-regrets" alternatives or immediately actionable options that should deliver adaptation benefits under any circumstances regardless of actual climate outcomes. For example, an early-warning system for natural disasters would be a suitable adaptation for any foreseeable future; it would constitute a "no-regrets" option (Ranger et al., 2010). Other plausible approaches include building flexibility into the adaptability measure, e.g., constructing infrastructure that could be modified in the future, if necessary, rather than rebuilt, or building flexibility into the decision-making process itself by taking no-regrets actions first and delaying more high-stakes actions until better information is available (Ranger et al., 2010). Doing so could help to avoid decisions that may become maladapted with time or limit further flexibility. Planned adaptation options may be the most appropriate in the face of low uncertainty, while generating adaptive capacity in a system might be a more appropriate strategy if there is high uncertainty of climate impacts. In any case, while uncertainty may complicate the decision-making process, it should not hinder it altogether.

Global impacts of climate change on agricultural production

We ranked the area harvested of the 50 most important crops reported by FAOSTAT (FAO, 2010b) and assessed their patterns of crop suitability using the EcoCrop model, following the procedure described by Ramírez-Villegas et al. (2011). The areas of each crop ranged from 26,290 to 2,161,000 km^2, and each had a wide range of physiological responses to climate, for example growing seasons (40–365 days), rainfall (200–8,000 mm/yr) and temperatures (2–48 °C). Within their environmental ranges (as indicated by EcoCrop), adaptation for a particular crop ranged from very marginal to highly suitable. We expected, therefore, to show the range of climatic response of each crop and estimate the likely effects of climate change on crop distribution.

We found that if crops were assumed to migrate without limit, global crop suitability increased by 0.84%, with buckwheat increasing most (+9.7%) and wheat decreasing most (-15.1%). At the global scale, 16 crops were less suitable, with wheat, sugar beet, white clover, and coffee becoming more than 10% less suitable, and no crop becoming more than 10% more suitable. Over half (26) of the crops were relatively insensitive to climate change (suitability changing less than 5%). Global changes in suitability may, however, vary from one region to another and 37 crops lost more than 50% of the area currently classified as suitable (Figure 1).

Trends in crop suitability also differed geographically. North Africa lost an average of 80% crop suitability, while Europe made the most important gains with no crop losing more than 5% suitability on average. Latin America, the Pacific, the Caribbean, and sub-Saharan Africa lost about 35–40% suitability overall, even allowing the crop area to migrate. Important issues of food security arise when crop suitability decreases significantly, especially in subtropics of the Mediterranean and India (Challinor et al., 2007).

Overall, the tropics become less suitable because critical thresholds of adaptability are exceeded in most marginally suitable areas (Figure 1). Predicted losses of more than 20% climate suitability will occur over 10, 15, 50, and 75% of the area currently growing cassava (Ceballos et al., 2011; Jarvis et al., 2012), bananas (Ramírez et

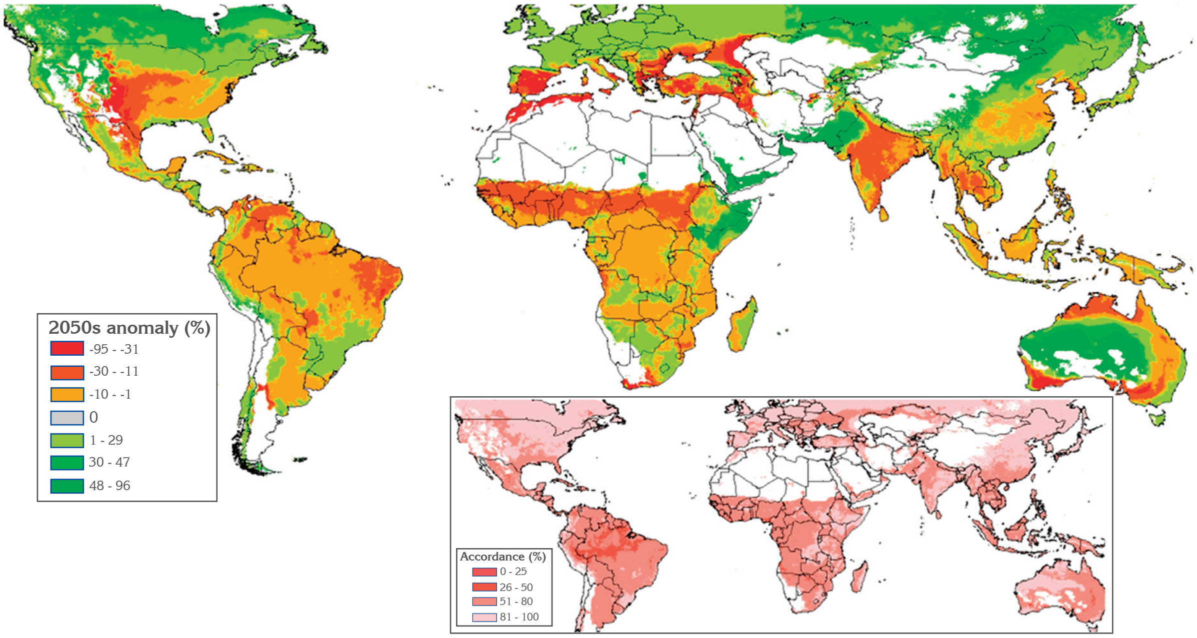

Figure 1. Average changes (main map) in climatic suitability by 2050s of the 50 most important crops globally (area basis), and accordance % (inset) of 18 global climate models.

al., 2011; Van den Bergh et al., 2012), potatoes (Schafleitner et al., 2011), and beans (Beebe et al., 2011), respectively. In contrast, black leaf streak, a major disease in bananas, is predicted to decrease by 3–7% in most banana-growing areas (Ramírez et al., 2011). Crop traits that the model flagged as important were: cold/water logging tolerance for cassava (Ceballos et al., 2011; Jarvis et al., 2012), cold/heat tolerance for bananas (Ramírez et al., 2011), heat/cold/drought tolerance for potatoes (Schafleitner et al., 2011), and heat/drought tolerance for beans (Beebe et al., 2011). Although cold tolerance may seem an odd trait when climate change predicts higher temperatures, at least some tropical crops may extend into the subtropics where cold snaps can damage sensitive crops (e.g., citrus in Florida).

In the past, farmers have adapted their cropping systems to tackle adverse climates and to respond to other environmental pressures. It is likely that they will continue to adapt their systems as the climate changes by adopting new varieties – or even new crops altogether – and by changing agronomic practices such as time of sowing (IPCC, 2007; Krishnan et al., 2007; Srivastava et al., 2010). There is a clear need to develop strategies to alleviate the negative impacts and capitalize on the positive impacts of climate change, particularly in the most vulnerable regions such as the tropics and subtropics. Adaptation strategies to overcome reduced crop suitability include:

- Changes in management to temporarily buffer negative climate change impacts
- Changes in infrastructure and timing, including modification of irrigation and drainage amounts, frequencies, and system types
- Modification of varieties in a well-defined regional breeding strategy, using both conserved genetic resources and molecular biotechnology to respond quickly to adaptation needs as they appear
- Changes in the intercropping, e.g., crop migration, taking into account economic and environmental sustainability

Another possibility is changing one or more of the components of the cropping system. Changing crops might be the only option available to poor smallholders, who are the most vulnerable, least able to adapt to rapid change, and most limited in access to new technology. Crop substitution therefore appears to be a key issue when addressing adaptation pathways for negatively impacted areas. It will be a challenge to produce well-adapted varieties that also comply with the many entrenched socio-cultural traditions that might prevent their adoption, such as regional preferences for size and color of beans in Mesoamerica (Thornton et al., 2011), or fruit characteristics in commercial bananas (Ramírez et al., 2011; Van den Bergh et al., 2012). Substitution of completely new crops will be even harder to bring about.

Given the significant shifts in the geographic suitability of crops, a considerable turnover in agricultural technologies and practices is likely to take place. The result could be more opportunities for piggy-backing change, both through appropriate deployment of technologies/practices and the creation of suitable incentive mechanisms that ensure that new agricultural systems deliver greater eco-efficiency. However, this poses the question: are climate change adaptation and mitigation measures always going to be eco-efficient?

Case study: End-to-end analysis of climate impacts and eco-efficient responses in Colombia

This section develops a concrete example of a climate change challenge and the possible response mechanisms to put to the test the hypothesis that eco-efficient agriculture is synonymous with climate change adaptation and on-farm mitigation interventions specific to the case of Colombia. First, climate impacts are assessed and the effects these have on crop suitability are quantified. Possible response mechanisms in the rice sector are then developed and tested economically and biophysically for their likely effectiveness in adapting to the various challenges.

Climate change scenarios for Colombia

Predicted climate changes

We extracted annual rainfall and mean annual temperature data for Colombia for two time slices – 2030 and 2050 (Figure 2) – from 19 global climate models (GCMs) forced with IPCC SRES scenario A2 (IPCC, 2007). SRES A2 is one of the less optimistic, "business-as-usual" scenarios based on continued regionally oriented economic and industrial intensification. Atmospheric concentrations of greenhouse gases (GHGs) over the 10 years since the SRES was

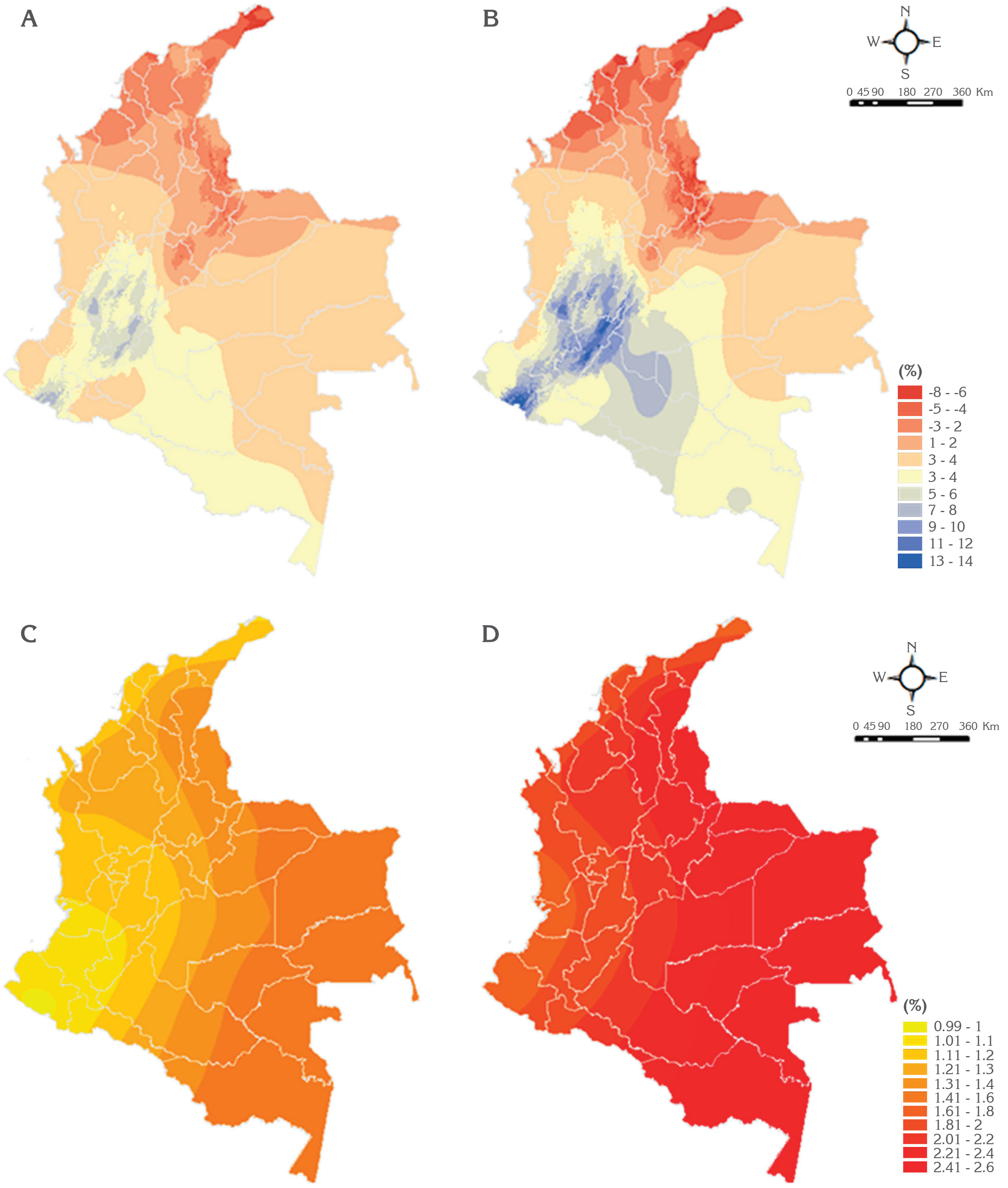

Figure 2. Changes in annual precipitation by (A) 2030 and (B) 2050, and in mean annual temperature by (C) 2030 and (D) 2050, predicted for Colombia under IPCC SRES emissions scenario A2. Average data based on 19 global climate models.

published broadly match the scenario's prediction. We emphasize that the predictions in the text that follows are derived from the GCMs and should be treated as such.

Precipitation in Colombia will likely decrease in some areas and increase in others for both time slices [Figures 29(A) and 2(B)]. In general, precipitation could decrease in the north by 40 mm/yr by 2030 and 90 mm/yr by 2050, while elsewhere it could increase by as much as 80 mm/yr by 2030 and 180 mm/yr by 2050.

The largest predicted decreases in annual precipitation are in the departments of Atlántico, Norte de Santander, Cesar, Sucre, Arauca, and Magdalena, and the largest increases will likely be in Valle del Cauca, Amazonas, Cauca, Quindío, Nariño, Tolima, Huila, and Caquetá. Precipitation patterns in 2030 and 2050 may be very similar to current patterns, though differing in magnitude, with ranges of -3 to +3% in 2030, and -6 to +5% in 2050.

Overall, mean annual temperatures are predicted to increase by 1.0–1.4 °C by 2030 and by 1.8–2.4 °C by 2050 (Table 1). Although mean annual temperatures will probably increase in all departments, the increase is likely to be greatest in Vaupés, Guainía, and Vichada for both 2030 and 2050 [Figures 2(C) and 2(D)].

Colombia is projected to warm 1.4–2.5 °C 2050, while precipitation is likely to vary between -6% and +5% in the current values. Distribution of precipitation is also likely to change, again varying by region. Temperature-sensitive crops may be affected by the higher temperatures and have to move to higher altitudes to avoid suffering significant losses of yield and quality. There will likely be trade-offs, e.g., with areas at or under 1,200 m altitude becoming less suitable for coffee than at present, while areas above 1,800 m become more suitable.

Uncertainty assessment

Although the GCMs are based on current understanding of the atmospheric processes, they do not implement that understanding in exactly the same way, causing their outputs to differ. The global climate change community deals with this by expressing the variation (i.e., spread) in the output as "uncertainty".[5] Uncertainty is a property of the external world, not the model itself, and as such it arises from a lack of data and/or knowledge about the initial conditions of the system, including the impossibility of modelling at a very high resolution (Challinor and Wheeler, 2008; Hawkins and Sutton, 2009; Majda and Gershgorin, 2010).

The uncertainties of the 19 GCMs for annual precipitation and annual mean temperature are shown in Figure 3. The dispersion between models for precipitation is high (Figure 3), especially along the Colombian Andes. This outcome is probably due to the complex topographic gradients of the Andean region, which cannot be resolved with such coarse models. Hence, some models project large increases and decreases in precipitation in highland areas, but only small changes in the country's lowlands, such as the Eastern Plains and the Caribbean regions. The result is high uncertainty for regions in the center of the country (Table 1).

The largest decreases in precipitation – up to 60 mm/yr by 2050 – are projected for the Caribbean region. The most pronounced increases are for the Amazon region and the coffee-growing zone: up to 130 mm/yr, although with relatively high uncertainty.

Although the scales are different, the uncertainty for mean annual temperature is relatively low when compared with the uncertainty for annual precipitation (see also Hawkins and Sutton, 2009; 2011 for a global analysis of uncertainty). Both

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[5] Although we are unable to represent exactly in a mathematical model how nature works, in this case the complex interactions of atmospheric circulation, there a number of different models that mimic the processes tolerably well. The results of these models can be expressed as a comparison between models (see e.g., Knutti et al., 2009; Meeh et al., 2007). There is an implicit understanding that the models used are approximations to what might be obtained from a thorough analysis if a fully adequate model of real-world processes were available.

Table 1. Changes in annual precipitation and mean annual temperature by 2030 and 2050 under IPCC SRES emissions scenario A2 for departments in Colombia.

		Precipitation (mm)					Temperature (°C)				
Region	Department	Current	Percent Change 2030	Range 2030	Percent Change 2050	Range 2050	Current	Change 2030	Range 2030	Change 2050	Range 2050
Amazon	Amazonas	4273.2	1.46%	305.4	2.45%	468.2	26.9	1.4	5.0	2.4	3.7
	Caquetá	3651.2	1.88%	716.2	3.55%	1196.8	24.9	1.3	3.9	2.2	2.8
	Guainía	2916.8	0.81%	363.8	1.45%	597.1	26.2	1.4	5.0	2.5	3.7
	Guaviare	3651.2	1.02%	457.2	2.30%	769.1	24.9	1.4	4.7	2.4	3.4
	Putumayo	3651.2	1.71%	986.1	3.29%	1701.7	24.9	1.1	3.0	2.0	1.9
	Vaupés	4273.2	0.74%	322.3	1.63%	470.7	26.9	1.4	5.0	2.5	3.6
Andean	Antioquia	4333.1	0.34%	424.9	0.64%	689.6	24.9	1.2	3.8	2.1	3.0
	Boyacá	5456.1	-0.38%	1095.7	-0.43%	1864.2	22.2	1.3	5.0	2.3	3.8
	Cundinamarca	5456.1	0.07%	1407.0	0.62%	2400.6	22.2	1.2	4.1	2.1	3.0
	Huila	5456.1	1.35%	863.7	2.53%	1370.6	22.2	1.1	2.7	1.9	1.8
	N. Santander	4333.1	-1.03%	698.7	-1.44%	1124.1	21.6	1.4	5.4	2.4	4.2
	Santander	4333.1	-0.43%	784.5	-0.64%	1369.9	24.9	1.3	5.3	2.3	4.0
	Tolima	5456.1	1.23%	678.4	2.15%	1232.7	22.2	1.1	3.1	1.9	2.4
Caribbean	Atlántico	971.7	-3.55%	335.3	-6.75%	613.5	26.5	1.1	2.5	1.8	2.2
	Bolívar	4333.1	-0.66%	323.1	-0.88%	539.7	24.9	1.3	4.3	2.2	3.4
	Cesar	4333.1	-0.89%	354.5	-1.28%	570.6	24.9	1.3	4.5	2.3	3.5
	Córdoba	4333.1	-0.60%	418.5	-0.85%	538.6	24.9	1.2	3.6	2.1	2.8
	La Guajira	971.7	-3.28%	286.7	-5.14%	446.5	26.5	1.2	3.0	1.9	2.6
	Magdalena	971.7	-3.70%	308.6	-6.23%	549.4	26.5	1.2	3.5	2.1	2.8
	Sucre	4333.1	-0.88%	355.8	-1.26%	502.3	24.9	1.2	3.9	2.1	3.0
Coffee-growing Zone	Caldas	5456.1	0.95%	629.6	1.61%	1028.0	22.2	1.2	3.6	2.0	2.9
	Quindío	5456.1	1.21%	492.5	1.87%	797.7	22.2	1.1	2.9	1.9	2.5
	Risaralda	5369.7	0.97%	493.6	1.52%	766.8	25.5	1.1	2.9	1.9	2.5
Eastern Plains	Arauca	2501.2	-1.25%	812.3	-2.17%	1394.6	26.0	1.4	5.6	2.5	4.5
	Casanare	5456.1	-0.14%	735.9	-0.08%	1233.5	22.2	1.4	5.2	2.4	4.0
	Meta	5456.1	0.72%	760.7	1.72%	1391.0	22.2	1.3	4.3	2.2	3.1
	Vichada	2916.8	0.39%	381.3	0.58%	553.4	26.2	1.4	5.0	2.5	3.9
Pacific	Chocó	5369.7	0.70%	466.6	1.04%	805.3	25.5	1.2	2.2	1.9	2.0
Southwest	Cauca	5369.7	1.15%	857.7	2.13%	1274.8	25.5	1.1	1.8	1.8	1.3
	Nariño	5265.0	1.25%	649.5	2.32%	1090.2	24.9	1.0	1.4	1.8	1.0
	Valle del Cauca	5369.7	1.15%	601.1	1.78%	1024.5	25.5	1.1	2.0	1.8	1.7

the differences between models and the standard deviation of their outputs vary longitudinally, increasing towards the east of the country, particularly in the Eastern Plains and the Amazon. The uncertainty in these two areas is also higher than elsewhere. The GCMs differ considerably – by up to 5 °C – in their projections for 2030 and 2050, although the mean of all models shows an increase of only half that by 2050. Differences between the GCMs, and thus their uncertainty, are relatively low in the southwest of the country.

GCM performance across Colombia

We cannot be certain which of the GCMs best represents the future climates. However, we can evaluate how well their output matches the baseline climates (1961–1990), i.e., present-day climates for which we have observational data.

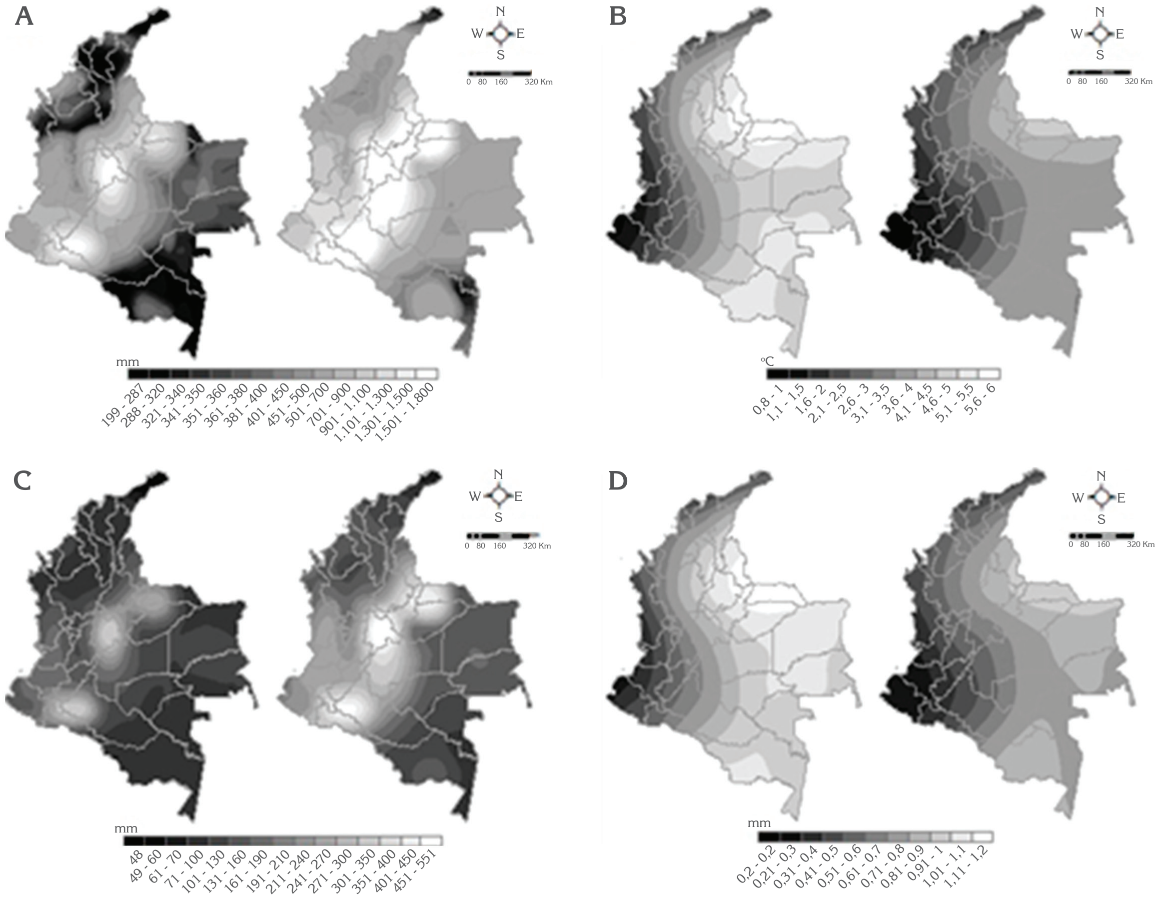

Figure 3. Uncertainty between global climate models for IPCC SRES scenario A2 for annual precipitation (A and C) and mean annual temperature (B and D). In each subfigure, the map on the left is for 2030 and the map on the right is for 2050. Subfigures A and B are the range between the global climate models and subfigures C and D are the standard deviations.

A simple way to evaluate the performance of climate models is to compare their results against observations.

We compared the results of each GCM with the readily-available climate databases WorldClim (Hijmans et al. 2005), Global Surface Summary of Day (GSOD) (Lott, 1998), Global Historical Climatology Network (GHCN) (Peterson and Vose, 1997; Lott, 1998), and Climate Research Unit (CRU) (Mitchell and Jones, 2005) following the methodology of Ramírez-Villegas et al. (2012) and Ramírez-Villegas and Challinor (2012) (Figure 4). We analyzed total rainfall and mean temperature over four seasons (Dec–Feb, Mar–May, June–Aug, Sept–Nov) and the whole year (ANN). For each model, the mean of all stations (GHCN and GSOD) or grid cells (WorldClim and CRU) was computed, GCM grid cells grouped, and the spatial consistency of the mean climate prediction assessed by calculating the determination coefficient (R^2) between the observed data and the GCMs. This coefficient defines the skill of each climate model to represent the climate of the baseline period.

The determination coefficient (R^2) for the baseline of annual precipitation is medium-high for the majority of the GCMs, especially for the interpolated surfaces (WorldClim and CRU), but is lower for the station data (GSOD and GHCN) because of their geographic distribution and relative scarcity (Figure 4). The GCMs perform slightly better for annual data, but less well for seasonal data, especially in the second semester (JJA–SON). At least 40% of the seasons and

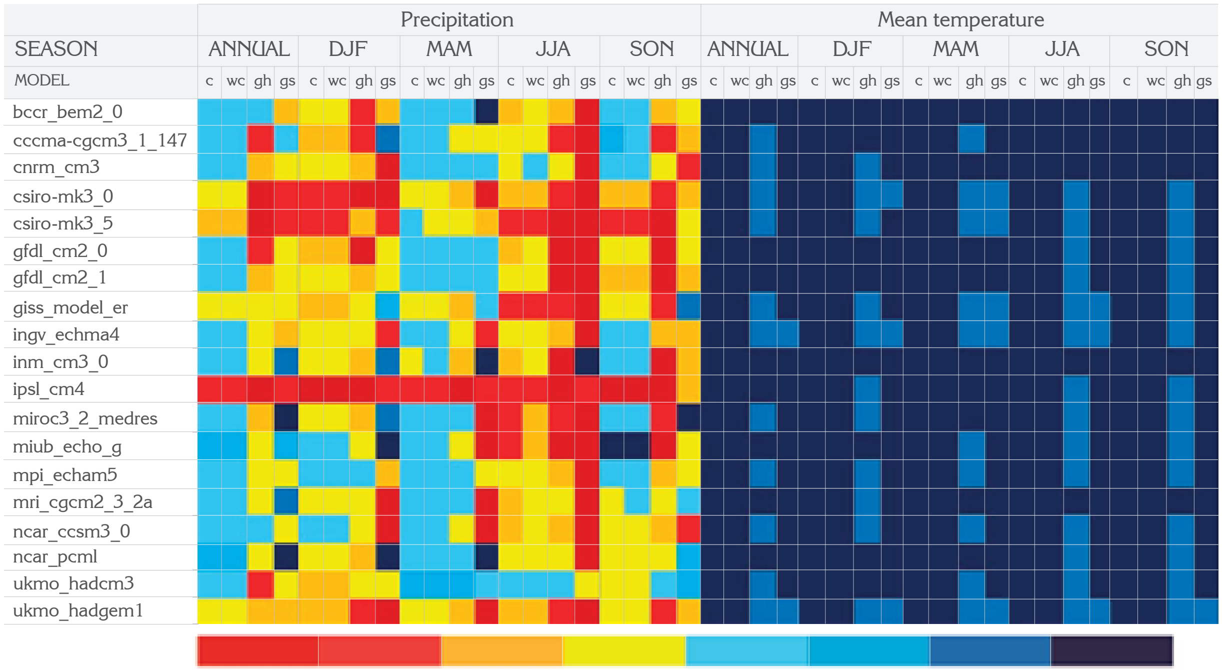

Figure 4. R^2 values for Climate Research Unit (CRU) interpolated surfaces (c), WorldClim interpolated surfaces (wc), Global Historical Climatology Network (GHCN) weather station data (gh), and Global Surface Summary of Day (GSOD) weather station data (gs) in relation to each global climate model over the 1961–1990 period.

GCMs perform poorly ($R^2<0.6$) for precipitation, and only 20% perform well ($R^2>0.8$). In contrast, R^2 for mean temperature is greater than 0.95 for all the models, both for the annual cycle and for seasons of the year (see also Ramírez-Villegas et al., 2012). We conclude that GCMs can generate data of mean future climates with moderately high precision for temperature and low precision for precipitation, although models still have a long way to go before they can predict Colombian climate variations accurately.

Climate change impacts on crops

We calculated the average change in climatic suitability for 25 crops selected for their importance in harvested area (ha) and production (t) in Colombia (Table 2), calculated averages for each department, and grouped them by region. We estimated the change in climate suitability using EcoCrop (Hijmans et al., 2001; Ramírez-Villegas et al., 2011) and applied the SRES A2 scenario for 2050 using data from 19 GCMs (Ramírez-Villegas and Jarvis, 2010). Current climate data were from WorldClim (Hijmans et al., 2005).

Overall, and using ±50% as the cutoff, losses in climate suitability between now and 2050 were greater than the gains. Losses could be seen in up to 82.7%, or about 945,790 km^2, of the country's total area (1,143,640 km^2), while the remaining 17.3% (197,850 km^2) should continue to have suitable climatic conditions for growing crops. The most critical regions are the Amazon, Caribbean, Pacific, and the Eastern Plains, where all departments are projected to have negative changes, although changes in several departments may be less than 15%. Changes will likely be positive in six of the seven Andean departments and all three of the coffee-growing region's departments: Caldas (3.8%), Risaralda (4.9%), and Quindío (12%).

It is useful for planning purposes to determine how many of the 25 crops analyzed are likely to become more suitable for the climate (winners), and how many are likely to become less suitable (losers) (Figure 5). In this case, the threshold of climate suitability – that is, a crop's climatic aptitude (CA) – for a winner or loser is ±5%. In

Table 2. Climatic suitability changes in potential agricultural area for each department in Colombia.

Region	Department	Change (%)	Potential area affected km^2	Potential area affected %
Amazon	Amazonas	-24.8	108,780	9.5
	Caquetá	-23.6	90,620	7.9
	Guainía	-27.8	70,680	6.2
	Guaviare	-19.6	55,830	4.9
	Putumayo	-23.8	25,460	2.2
	Vaupés	-28.4	53,100	4.6
Andean	Antioquia	-5.7	63,700	5.6
	Boyacá	12.2	22,140	1.9
	Cundinamarca	3.6	22,550	2.0
	Huila	3.3	18,320	1.6
	Norte de Santander	0.5	21,980	1.9
	Santander	-0.1	30,470	2.7
	Tolima	2.0	23,610	2.1
Caribbean	Atlántico	-24.6	3,420	0.3
	Bolívar	-14.8	27,150	2.4
	Cesar	-12.9	22,880	2.0
	Córdoba	-15.8	25,300	2.2
	La Guajira	-34.7	20,840	1.8
	Magdalena	-17.1	23,000	2.0
Coffee-growing Zone	Caldas	3.8	7,390	0.6
	Quindío	12.0	1,930	0.2
	Risaralda	4.9	3,470	0.3
Eastern Plains	Arauca	-19.2	23,670	2.1
	Casanare	-16.7	44,670	3.9
	Meta	-16.3	85,960	7.5
	Sucre	-15.3	10,890	1.9
	Vichada	-15.5	100,100	8.8
Pacific	Chocó	-9.6	28,940	2.5
Southwest	Cauca	6.3	26,650	2.3
	Nariño	-3.4	30,470	2.7
	Valle del Cauca	1.8	17,370	1.5

Note: Total percentage of area potentially affected would be 97.3% (1,112,800 km^2).

some departments in the Andean and Pacific regions (Antioquia, Boyacá, Cauca, Cundinamarca, Nariño, and Valle del Cauca), 7–10 crops covering 1.6 million ha could gain in CA. In the departments of La Guajira, Cesar, and Bolívar in the country's Caribbean region, 9–13 crops covering 440,000 ha could decrease in CA. About 72 million ha show uncertainty (coefficient of variability between models) less than 30%, mostly in the Andean and Eastern Plains regions, which represent most of the country's agricultural activity.

Climate-smart adaptation and mitigation options for rice systems in Colombia

Colombian rice systems

Rice ranks first among short-cycle crops in terms of its importance to Colombia's economy.

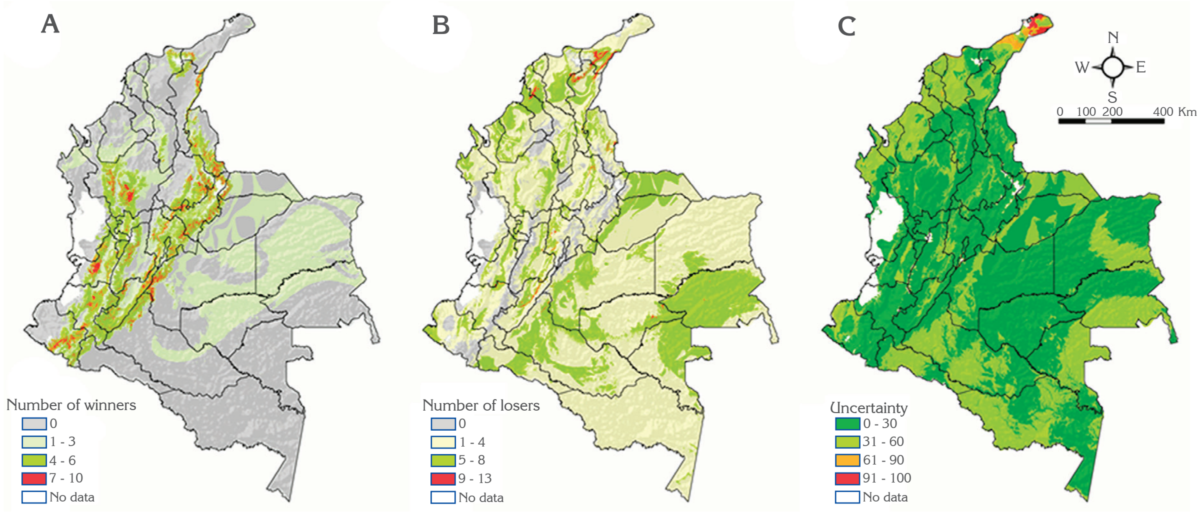

Figure 5. Changes in the suitability of 25 crops in Colombia estimated with EcoCrop: (A) climate more suitable; (B) climate less suitable; and (C) estimates of uncertainty (Coefficient of Variation, CV).

The country is the second largest rice producer in Latin America, and even so is a net rice importer. Rice is the primary source of calories for the low-income group, which accounts for over 37% of Colombia's population (The World Bank, 2012). The two predominant systems of rice production in Colombia are mechanized – which includes both irrigated and rainfed systems – and manual, with all production activities being undertaken with hand labor. In 2007, Colombia produced 2,471,545 tons of rice on over 400,000 ha of land (Fedearroz, 2007).

An expert workshop on climate change at the International Center for Tropical Agriculture (CIAT) identified two potential climate-smart adaptation pathways for rice in Colombia: irrigation of traditional dryland rice and genetic modification for high-temperature tolerance. We also considered three mitigation measures for rice in Colombia: managing flooded rice to minimize CH_4 emissions, eliminating burning of crop residues, and optimizing the amount of applied fertilizer.

Types of economic analyses

Two important tools for selecting and prioritizing "no-regrets" adaptation or mitigation options are cost–benefit analysis (CBA) and cost-efficiency analysis (CEA). For adaptation purposes the most relevant analysis is usually the CBA, which asks whether the returns (benefits, such as avoided damage/losses or extra developmental benefits compared with "business as usual") are greater than the costs (extra investment compared with "business as usual"), and by how much. CBA quantifies all costs and benefits of an intervention with monetary values, making it appropriate when economic efficiency is the only decision-making criteria (UNFCCC, 2011).

The impact of climate change on crops can be quantified with modelling, as can the extent to which impacts can be avoided through one or more adaptation options. Thus the most effective adaptation option can be chosen based on a discrete comparison of the cost of implementing the adaptation measure and its resulting benefits (improvement in crop production, avoidance of economic losses). Elements of climate change mitigation, on the other hand, are not always so easy to express in monetary terms. For example, the benefits of reduced GHG emissions are not restricted to the site of the emissions but are global in their effects, making them difficult to estimate (it is not yet possible to estimate GHG emission damages by modelling at the specific local level and then extrapolating globally). Positive environment-, health-, or livelihood-related outcomes cannot be valued in a strictly monetary sense because they are not localized in the way that adaptation benefits are.

CEA is useful for situations in which there is a concrete objective and where impacts are measurable but benefits are not (UNFCCC 2011), as is the case with many mitigation measures. The costs in a CEA can be valued in monetary terms, but the benefits must be expressed in “physical” units. It is then possible to construct a cost-efficiency curve that can be used to identify and prioritize those mitigation measures that are economically viable for achieving a well-defined physical target.

Cost–benefit analysis of adaptation options

Out of the area under rice production in Colombia, 256,295 ha (64%) are irrigated and 29,556 ha (36%) are dryland/rainfed (Fedearroz, 2007). The potential area for irrigation based on water availability and climate is estimated to be 6.6 million ha (AQUASTAT, 2010). Dryland rice will be vulnerable to yield losses from water stress caused by climate change, i.e., increased evapotranspiration due to higher temperatures and compounded by lower overall rainfall. Furthermore, the introduction of modern seed varieties has seen dryland rice lose competitiveness with irrigated systems; the average yield gap between irrigated and dryland systems can be more than 4 t/ha (Lang, 1996).

We simulated the effects of climate change for dryland rice with the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003), using the variety and agronomy currently recommended by the National Federation of Rice Growers (Fedearroz, its Spanish acronym). We first simulated the effect of climate change without irrigation and subsequently its effect with irrigation. We estimated the costs of providing irrigation in terms of the initial investment required and the costs of operation and maintenance with a life span of 20 years. We calculated the benefits of the irrigation project as the difference between rice production with and without irrigation under the SRES scenario A2. We calculated operation and maintenance costs and estimated an increase of 1% annually, using an annual discount rate of 12%.

Analysis of the financial flow shows that building an irrigation system in the Colombia’s Caribbean and Eastern Plains regions gives positive net present values (Figure 6), and in each case the development would be financially viable.

The second adaptation measure that we tested was a research program to seek and develop, by 2030, new rice varieties tolerant of higher temperatures. The rising temperatures expected from climate change pose a threat to rice production by increasing the risk for spikelet sterility during development. However, rice germplasms exhibit great variability in their response to heat stress. Heat-tolerant cultivars have been shown to respond well to increased temperatures while still producing economic yield

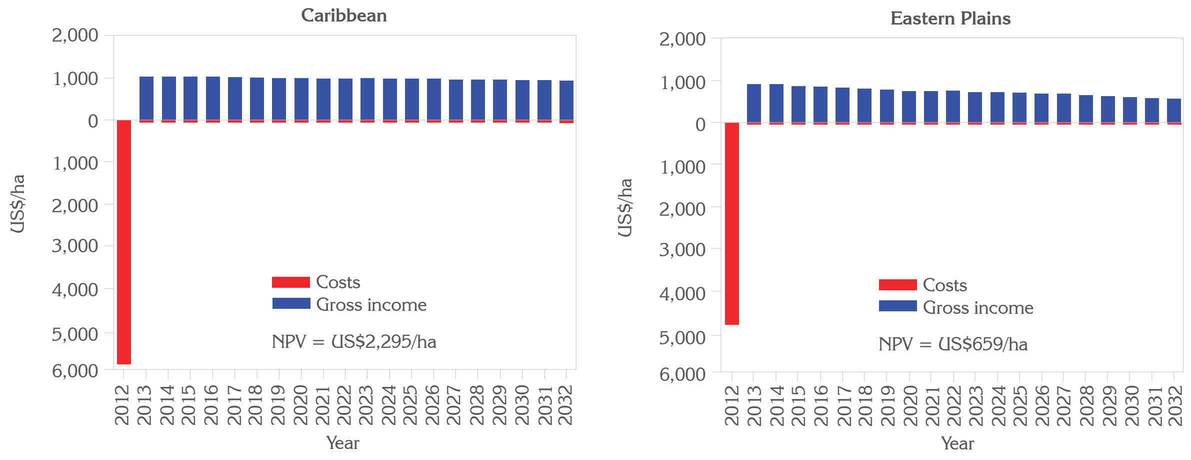

Figure 6. Costs and benefits year by year for an irrigation system project in Colombia’s Caribbean and Eastern Plains regions, and net present value (NPV) with a social discount rate of 12%.

(Shah et al., 2011). Furthermore, improved cultivars could potentially offset stress from increased evapotranspiration by exhibiting better water use efficiency, greater harvest indices, and deeper/faster-growing roots.

We used the costs of a 26-year research program (including researchers, assistants, field workers, materials, infrastructure, and operational and administrative costs) and simulated the yields in 2050 of the currently recommended variety and a synthetic variety less sensitive to temperature using DSSAT.[6] We calculated the benefit as the economic value of the difference in production between the current and the synthetic varieties. We assumed a progressively decreasing rate of adoption with a final level of adoption of 15% for the whole country and a discount rate of 12% annually.

The cost–benefit analysis shows that it is highly desirable to mount a research program to improve the resistance of rice to high temperatures, giving a large net present value (Figure 7).

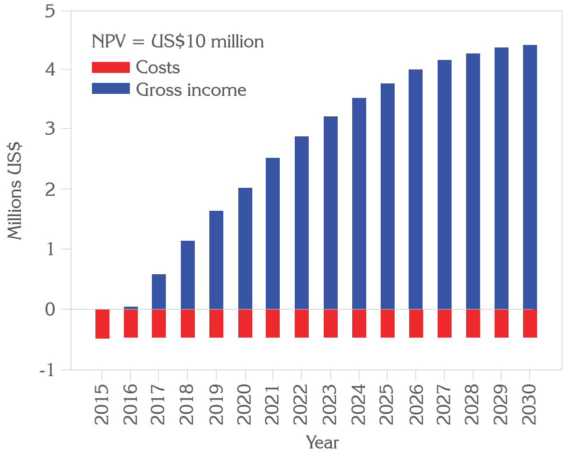

Figure 7. Costs and benefits year by year for a research program to increase the resistance of rice to high temperatures, and net present value (NPV) with a social discount rate of 12%.

Cost-efficiency analysis of mitigation options

CEA assesses the economic costs and the technical efficiency of different options to achieve some predetermined level of environmental quality. The analysis assists the decision-making process by allowing feedback from those affected by a proposed program or plan of action to revise the objectives as part of the process. CEA allows the construction of curves of marginal cost, which are obtained by ordering all possible alternative actions according to their cost and their effect on the environmental factor under consideration. In the case of the reduction of GHG emissions in agriculture, the options can be modelled using the *Cool Farm Tool,* (www.coolfarmtool.org/Home), a tool originally developed by Unilever and researchers at the University of Aberdeen to help growers measure and understand on-farm GHG emissions.

Calculations of methane emissions reduction are based on empirical evidence collected from Colombian literature. Calculations of nitrogen/yield relationships are based on modelling of potential yield under different treatments using the DSSAT CERES-Rice model. Quantifications of on-farm production in the different regions of Colombia are drawn from Fedearroz survey data.

Data from the field have shown that flooded rice generates greater emissions of CH_4 than rice grown with intermittent irrigation (or irrigation interspersed with dry periods), which allows soil aeration and is unfavorable for the anaerobes that produce CH_4. Flooded rice in Colombia is typically grown in the municipalities of Jamundí (Valle del Cauca) and Cúcuta (Santander). Substituting of intermittent irrigation for continuous flooding requires the following: (1) implementation of a system of monitoring and water use control at the

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[6] DSSAT largely represents the effects of temperature on rice as its effect on the development rate, in which higher temperatures shorten the duration of the various growth stages. We arbitrarily altered the genetic coefficients in DSSAT to make a synthetic variety that was less sensitive to temperature by increasing the genetic coefficients P1 and P5 by 15%. Coefficient P1 is the time period [expressed as growing degree days (GDD) above a base temperature of 9 °C] from seedling emergence during which the rice plant is not responsive to changes in photoperiod. This period is also referred to as the basic vegetative phase of the plant. Coefficient P5 is the time period in GDD from the beginning of grain filling (3 to 4 days after flowering) to physiological maturity with a base temperature of 9 °C.

level of the individual field; (2) training and field demonstrations of land preparation and the use of water budgeting balance; and (3) land preparation for more efficient water use. The cost to implement these measures is US$107/ha per year, which will reduce GHG emissions by 11.65 t CO_2 eq/ha per year in Cúcuta and 13.06 t CO_2 eq/ha per year in Jamundí. The estimated cost efficiency is \$9.20/t CO_2 eq per ha per year in Cúcuta and \$8.21/t CO_2 eq per ha per year in Jamundí. The maximum potential reduction of emissions is 197,050 t CO_2 eq/yr for Cúcuta and 66,810 t CO_2 eq/yr for Jamundí.

Harvest residues are typically burned in the municipalities of Espinal (Tolima), Valledupar (Cesar), and Yopal (Casanare). Instead of burning, residues can be managed using minimum tillage and decomposition accelerators, which, including training, costs US$112 for Espinal and Valledupar, and US$57 for Yopal. The reductions of GHG emissions are 0.95, 0.53, and 0.47 t CO_2 eq/ha per year for Espinal, Valledupar, and Yopal, respectively, with estimated cost efficiencies of \$59, \$104, and \$120/t CO_2 eq per ha per year. The potential reduction of GHG emissions is 26,270 t CO_2 eq/yr for Espinal, 3,280 t CO_2 eq/yr for Valledupar, and 3,300 t CO_2 eq/yr for Yopal.

There are many factors that affect rice's nitrogen use efficiency (NUE), or its ability to absorb and use nitrogen inputs. The result is often that more fertilizer is applied than can be used by the plant, or that not enough is applied to get maximum yields and economic returns. There are three possible approaches for increasing the efficiency of nitrogen fertilizer application to rice in Colombia, thereby reducing unnecessary inputs and decreasing emissions from crop fertilization (Figure 8). The first involves reducing overall nitrogen application, which increases NUE but entails reduction in rice yields (scenario A). The second requires no reduction or increase in nitrogen application, but requires more-effective management techniques so that what does get applied is used effectively by the plant (scenario B). The final approach involves both increasing nitrogen inputs and NUE through better management to arrive at optimum economic returns from the system (scenario C). All three scenarios are climate smart – they result in fewer emissions per ton of rice produced due to optimal N uptake – however we will only be analyzing scenario A for economic viability and relative eco-efficiency.

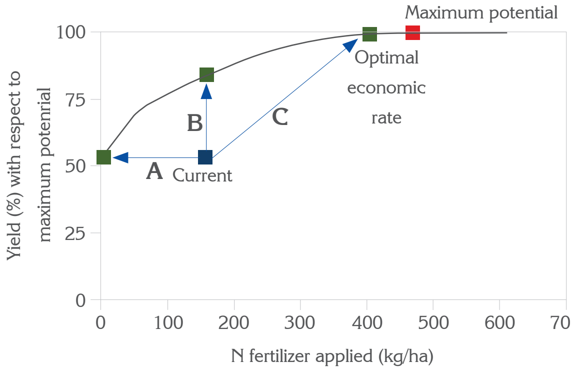

Figure 8. Potential yield achieved under different application levels of nitrogen, based on modelling crop response with the DSSAT CERES-Rice model. The arrows represent different approaches for increasing efficiency of nitrogen fertilizer application in rice systems: A) Decreased N input but increased use efficiency maintains a stable yield, B) Same N input, with increased NUE and reduction of yield gap through optimal management, and C) increased N input to economic optimal levels, with associated increased NUE and increased management.

It is possible to halve the rates of fertilizer applied to rice in two regions of Colombia: the Andean and Caribbean regions. The cost of this option is estimated using the following equation:

$$C_r = \sum_{s=1}^{2} (\nabla R_s * \overline{P}_S - \nabla \mathrm{F}_r * \mathrm{Z}_r)$$

where:

C_r= annual cost of measure C in region r (US$/ha);

$\nabla \mathrm{F}_r$ = reduction of 50% of the mean fertilizer of the region in each cropping cycle (kg/ha);

∇R_{rs} = change in yield of the crop in region r in semester s as simulated in DSSAT due to the 50% reduction in fertilizer (t/ha);

Z_r = mean price of fertilizer in 2010 (US$/ton);

$\bar{P}s$ = mean value of rice in semester *s* (during the last 10 yr in constant 2010 US\$/ton).

The estimated costs of this option in terms of foregone production are: Andean, US\$113/ha per year, and Caribbean, \$183/ha per year. The expected reduction of GHG emissions are: Andean, 1.0 t CO_2 eq/ha per year, and Caribbean, 0.2 t CO_2 eq/ha per year. Nevertheless, the estimates of cost efficiency are \$109 and \$170/t CO_2 eq reduced for the Andean and Caribbean regions, respectively. The maximum potential reduction of GHG emissions is 76,170 and 2,920 t CO_2 eq/yr for the Andean and Caribbean regions, respectively.

It is important to keep in mind that the yield reductions caused by decreased nitrogen inputs have further repercussions for global food security. There is a possibility that reducing N application in one region or country could simply displace GHG emissions to another, which would have to produce more to make up for the decrease in yield, a factor which was not taken into account in this analysis.

The data for the three mitigation options in various departments in Colombia are summarized in Figure 9.

The priority adaptation and mitigation interventions identified for the rice sector all involve optimization of resource inputs and outputs, be it fertilizers or water, or improved use of "waste" products. The economic analysis demonstrates the cost-benefit ratios of these interventions from a climate change mitigation perspective, but equally could consider these from a competitiveness perspective, or prioritize them based on eco-efficiency principles.

Eco-efficiency of climate-smart practices

Although the practices described above are already considered climate smart, our definition of the term leaves room for the possibility that, though a strategy may be climate smart, it may not necessarily be economically viable, environmentally sustainable, or make good use of resources. As noted by Keating et al. in Chapter 2 of this publication, eco-efficiency is a multifaceted concept that is characterized by a variety of

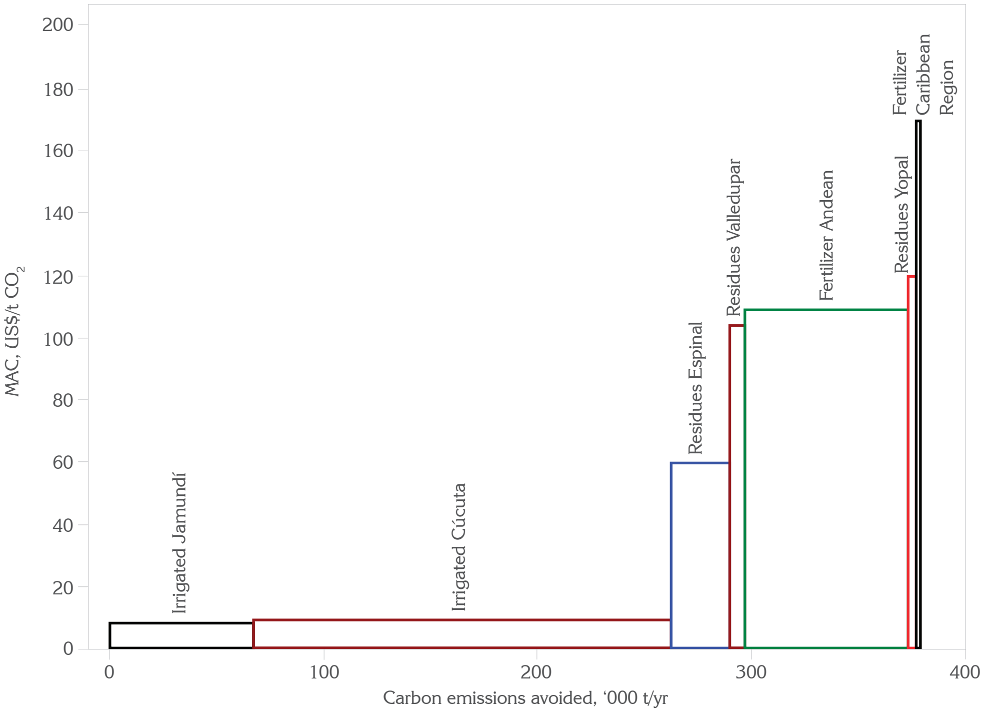

Figure 9. Marginal abatement curves (MAC) (US\$/t CO_2 eq) for various interventions in rice culture in Colombia.

potential measures. Thus, while an eco-efficient practice is highly likely to also be climate smart, some climate-smart practices are probably more eco-efficient than others if a number of such measures are taken into account.

Making use of some of the explicit measures noted by Keating et al. (Chapter 2 of this publication), we attempted to qualitatively evaluate the climate-smart adaptation and mitigation measures chosen for Colombia based on their relative eco-efficiency. A measure of eco-efficiency must be made with regard to the relation of inputs, such as labor, capital, nutrients, and water; with desired outputs, such as harvested product or economic profit. Table 3 gives a positive or negative value for the eco-efficiency measures to each of the 5 climate-smart practices; a negative value (red) is assigned when a practice requires more inputs (+) or results in less of the desired outputs (-), whereas a positive value (green) is assigned for a reduction in inputs (-) or increase in desired outputs (+).

Table 3 shows that not all of the climate-smart strategies chosen for Colombia are highly eco-efficient, though some are more so than others.

For example, the composting of crop residues in the field instead of burning appears to be highly eco-efficient – as it both reduces the amount of input required in terms of labor, water, and soil nutrients, and increases outputs in the form of ecosystem services. This inference is confirmed by the cost-efficiency analysis, which shows that eliminating residue burning it is capable of greatly reducing GHG emissions at a very reasonable cost to the farmer.

Conclusions

Despite the built-in uncertainties of global climate models, there is a reasonable amount of evidence to support the prediction that global temperatures could rise anywhere from 1 to 8 °C by 2050. Precipitation patterns are less predictable, though certain scenarios can predict with high certainty a global average increase of almost 23% by 2050, along with major changes in spatio-temporal distribution. Circumstances at the country level are similar, with Colombia predicted to undergo temperature increases between 1.4 and 2.5 °C by 2050, shifting distributions of rainfall, and a range of regional precipitation changes (-6 to +5%).

Table 3. Eco-efficiency ratings for adaptation/mitigation strategies in Colombian rice systems.

Eco-efficiency measure		Irrigation of dryland rice	Heat-tolerant variety	Intermittent irrigation	Residue re-use	Nitrogen efficiency
Inputs	Land area	-	-	0	0	+
	Soil nutrients	+	0	0	-	-
	Water	+	0	+	-	0
	Energy	-	0	0	0	-
	Labor	+	0	+	0	0
	Capital	+	+	0/+	0	-
Outputs	Production (rice yield)	+	+	+	0	-
	Profit or return on investment	+	+	0/+	0/+	0
	Security of food system	+	+	0	0	🟥
	Nutritional quality	0	0	0	0	0
	Ecosystem services	0/-	0	+	+	+
	Eco-efficiency rating	0.5	3	0	3.5	1

Desirable	1
	0.5
	0
	-0.5
Undesirable	-1

The implications of these changes for world agriculture could be profound, with some 37 of the most important crops predicted to lose more than 50% of area currently classified as suitable for their cultivation. Colombia could experience losses in crop suitability in up to 83% of the country's total area, especially in the Amazon, Pacific, Caribbean, and Eastern Plains regions. In these regions, adaptation strategies will undoubtedly be necessary to cope with the impacts of decreased crop suitability.

Economic analyses of preferred adaptation and mitigation strategies for Colombian agriculture give encouraging results. Both the adoption of an irrigation system and the development of a research program for heat-resistant rice are economically viable, and, in the latter case, highly profitable in the mid-term. Mitigation strategies offer a more mixed bag: replacing flooded rice with intermittent irrigation reduces emissions at a relatively low cost. Using minimum tillage and decomposition accelerators instead of burning residues greatly reduces emissions, but at a higher cost.

Climate change necessitates the implementation of adaptation/mitigation measures to ensure food security. The critical question is whether these climate-smart strategies and measures that meet the standards of eco-efficiency are mutually inclusive. To be sure, many of the resources that eco-efficiency aims to manage prudently (water, nutrients, labor, finances, etc.) are the same resources that must be managed for adaptation/mitigation purposes. For example, using minimum tillage and decomposers in Colombian rice fields instead of burning crop residues after harvest is eco-efficient because it greatly reduces the inputs of water and labor required for conventional puddled transplanting systems while leaving yields virtually unaffected (Bhushan et al., 2007). The practice advances mitigation goals at the same time; omitting tillage and burning considerably reduces carbon emissions.

Qualitatively evaluating the eco-efficiency of the climate-smart strategies chosen for Colombia in terms of the balance of inputs and outputs indicates that, while most eco-efficient practices are by default climate smart, not all climate-smart practices are necessarily highly eco-efficient. Instead, climate-smart practices display a range of compatibility with eco-efficient measures. While some, like the more precise application of nitrogen fertilizer, could result in significant reduction of inputs (soil nutrients, capital, labor, etc.) while augmenting desirable outputs, others may imply more labor, greater financial risk, or even unexpected environmental costs. Accordingly, those options which are a win for both system types should be emphasized in climate change planning to avoid the possibility of adaptation/mitigation coming at the price of efficiency and food security. Furthermore, climate financing could provide a boost to eco-efficient agriculture, thus opening the door for economic incentives to transform low-efficiency systems.

References

AQUASTAT. 2010. Sistema de información sobre el uso del agua en la agricultura y el medio rural de la FAO. Food and Agriculture Organization of the United Nations. Rome, Italy.

Beebe S; Ramírez-Villegas J; Jarvis A; Rao IM; Mosquera G; Bueno JM; Blair MW 2011. Genetic Improvement of Common Beans and the Challenges of Climate Change. In: Yadav SS; Redden R; Hatfield JL; Lotze-Campen H; Hall A, eds. Crop adaptation to climate change. Wiley-Blackwell, Oxford, UK. p 356–369.

Bhushan L; Ladha JK; Gupta RK; Singh S; Tirol-Padre A; Saharawat YS; Gathala M; Pathak H. 2007. Saving of water and labor in a rice–wheat system with no-tillage and direct seeding technologies. Agronomy Journal 99(5):1288–1296.

Ceballos H; Ramírez-Villegas J; Bellotti AC; Jarvis A; Alvarez E. 2011. Adaptation of Cassava to Changing Climates. In: Yadav SS; Redden R; Hatfield JL; Lotze-Campen H; Hall A, eds. Crop adaptation to climate change. Wiley-Blackwell, Oxford, UK. p 411–425.

Challinor AJ; Wheeler TR. 2008. Crop yield reduction in the tropics under climate change: Processes and uncertainties. Agricultural and Forest Meteorology 148(3):343–356.

Challinor AJ; Wheeler TR; Craufurd PQ; Ferro CAT; Stephenson DB. 2007. Adaptation of crops to climate change through genotypic responses to mean and extreme temperatures. Agriculture, Ecosystems & Environment 119(1–2):190–204.

Challinor AJ; Osborne T; Shaffrey L; Weller H; Morse A; Wheeler T; Vidale PL. 2009. Methods and resources for climate impacts research. Bulletin of the American Meteorological Society 90(6): 836–848.

Cooper PJM; Stern RD; Noguer M; Gathenya M. 2012. Supporting evidence-based research in sub-Saharan Africa for the adaptation of rainfed agriculture to climate change: Laying the foundations stones of success. In press.

FAO (Food and Agriculture Organization of the United Nations). 2010a. “Climate-smart” agriculture: Policies, practices and financing for food security, adaptation and mitigation. Rome, Italy.

FAO (Food and Agriculture Organization of the United Nations). 2010b. FAOSTAT. (Ed FAO). Rome, Italy.

Fedearroz (National Federation of Rice Growers). 2007. III Censo nacional arrocero: Cubrimiento cosecha A-B, 2007. Bogotá D.C., Colombia.

Garrett KA; Dobson ADM; Kroschel J; Natarajan B; Orlandini S; Tonnang HEZ; Valdivia C. 2012. The effects of climate variability and the color of weather time series on agricultural diseases and pests, and on decisions for their management. Agricultural and Forest Meteorology. DOI:10.1016/j.agrformet.2012.04.018.

Gleckler PJ; Taylor KE; Doutriaux C. 2008. Performance metrics for climate models. Journal Geophys Research Atmosphers 113(D6):D06104.

Hawkins E; Sutton R. 2009. The Potential to Narrow Uncertainty in Regional Climate Predictions. Bulletin of the American Meteorological Society 90(8):1095–1107.

Hawkins E; Sutton R. 2011. The potential to narrow uncertainty in projections of regional precipitation change. Climatic Dynamics 37(1):407–418.

Hijmans RJ; Guarino L; Cruz M; Rojas E. 2001. Computer tools for spatial analysis of plant genetic resources data: 1. DIVA-GIS. Plant Genetic Resources Newsletter 127:15–19.

Hijmans RJ; Cameron SE; Parra JL; Jones PG; Jarvis A. 2005. Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25(15):1965–1978.

Hutchinson JJ; Campbell CA; Desjardins RL. 2007. Some perspectives on carbon sequestration in agriculture. Agricultural and Forest Meteorology 142(2–4):288–302.

IPCC (Intergovernmental Panel on Climate Change). 2000. Special report on emissions scenarios. Geneva, Switzerland. Available at: www.ipcc.ch/pdf/special-reports/spm/sres-en.pdf

IPCC (Intergovernmental Panel on Climate Change). 2007. IPCC Fourth Assessment Report: Climate Change 2007 (AR4). Geneva, Switzerland.

Jarvis A; Lau C; Cook S; Wollenberg E; Hansen J; Bonilla O; Challinor A. 2011. An Integrated Adaptation and Mitigation Framework for Developing Agricultural Research: Synergies and Trade-offs. Experimental Agriculture 47(02): 185–203.

Jarvis A; Ramírez-Villegas J; Herrera Campo B; Navarro-Racines C. 2012. Is Cassava the Answer to African Climate Change Adaptation? Tropical Plant Biology 5(1):9–29.

Jones JW; Hoogenboom G; Porter CH; Boote KJ; Batchelor WD; Hunt LA; Wilkens PW; Singh U; Gijsman AJ; Ritchie JT. 2003. The DSSAT cropping system model. European Journal of Agronomy 18(3–4):235–265.

Jones PG; Thornton PK. 2009. Croppers to livestock keepers: livelihood transitions to 2050 in Africa due to climate change. Environmental Science & Policy 12(4):427–437.

Key N; Tallard G. 2012. Mitigating methane emissions from livestock: a global analysis of sectoral policies. Climatic Change 112(2):387–414.

Knutti R; Furrer R; Tebaldi C; Cermak J; Meehl GA. 2009. Challenges in Combining Projections from Multiple Climate Models. Journal of Climate 23(10):2739-2758.

Krishnan P; Swain DK; Chandra Bhaskar B; Nayak SK; Dash RN. 2007. Impact of elevated CO_2 and temperature on rice yield and methods of adaptation as evaluated by crop simulation studies. Agriculture, Ecosystems & Environment 122(2):233–242.

Lal R. 2004. Soil Carbon Sequestration Impacts on Global Climate Change and Food Security. Science 304(5677):1623–1627.

Lang J. 1996. Feeding a hungry planet: Rice, research and development in Asia and Latin America. Chapel Hill: University of North Carolina Press. USA.

Lobell DB; Burke MB; Tebaldi C; Mastrandrea MD; Falcon WP; Naylor RL. 2008. Prioritizing Climate Change Adaptation Needs for Food Security in 2030. Science 319(5863):607–610.

Lobell DB; Sibley A; Ortiz-Monasterio JI. 2012. Extreme heat effects on wheat senescence in India. Nature Climate Change 2:186–189.

Lott N. 1998. Global surface summary of day. National Climatic Data Center (NCDC). Asheville, North Carolina, USA. Available at: www.ncdc.noaa.gov/cgi-bin/res40.pl?page=gsod.html

Majda AJ; Gershgorin B. 2010. Quantifying uncertainty in climate change science through empirical information theory. Proceedings of the National Academy of Sciences of the United States of America 107(34):14958–14963.

Meehl GA; Stocker TF; Collins WD; Friedlingstein P; Gaye AT; Gregory JM; Kitoh A; Knutti R; Murphy JM; Noda A; Raper SCB; Watterson IG; Weaver AJ; Zhao Z. 2007. Global Climate Projections. In: Solomon S; Qin D; Manning M; Chen Z-C; Marquis M; Averyt KB; Tignor M; Miller HL, eds. Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). Cambridge University Press, UK; New York, NY, USA.

Mitchell TD; Jones PD. 2005. An improved method of constructing a database of monthly climate observations and associated high-resolution grids. International Journal of Climatology 25(6): 693–712.

Moorhead A. 2009. Climate, agriculture and food security: A strategy for change. Consultative Group on International Agricultural Research. Montpellier, France. Available at: http://www.cgiar.org/www-archive/www.cgiar.org/pdf/CCAFS_Strategy_december2009.pdf

Moss RH; Edmonds JA; Hibbard KA; Manning MR; Rose SK; van Vuuren DP; Carter TR; Emori S; Kainuma M; Kram T; Meehl GA; Mitchell JFB; Nakicenovic N; Riahi K; Smith SJ; Stouffer RJ; Thomson AM; Weyant JP; Wilbanks TJ. 2010. The next generation of scenarios for climate change research and assessment. Nature 463(7282): 747–756.

Ortiz R; Sayre KD; Govaerts B; Gupta R; Subbarao GV; Ban T; Hodson D; Dixon JM; Ortiz-Monasterio JI; Reynolds M. 2008. Climate change: Can wheat beat the heat? Agriculture, Ecosystems & Environment 126(1–2):46–58.

Peterson TC; Vose RS. 1997. An Overview of the Global Historical Climatology Network Temperature Database. Bulletin of the American Meteorological Society 78(12):2837–2849.

Pye-Smith C. 2011. Farming's climate-smart future. Technical Centre for Agricultural and Rural Cooperation (CTA). Wagenigen, The Netherlands. Available at: http://ccafs.cgiar.org/sites/default/files/assets/docs/farmings_climate-smart_future.pdf

Ramírez J; Jarvis A; van den Bergh I; Staver C; Turner D. 2011. Changing Climates: Effects on Growing Conditions for Banana and Plantain (*Musa* spp.) and Possible Responses. In: Yadav SS; Redden R; Hatfield JL; Lotze-Campen H; Hall A, eds. Crop adaptation to climate change. Wiley-Blackwell, Oxford, UK. p 426–438.

Ramírez-Villegas J; Challinor A. 2012. Assessing relevant climate data for agricultural applications. Agricultural and Forest Meteorology 161:26–45.

Ramírez-Villegas J; Jarvis A. 2010. Downscaling global circulation model outputs: The delta method. Decision and Policy Analysis Working Paper No. 1. CIAT, Cali, Colombia. http://www.ccafs-climate.org/downloads/docs/Downscaling-WP-01.pdf

Ramírez-Villegas J; Jarvis A; Läderach P. 2011. Empirical approaches for assessing impacts of climate change on agriculture: The EcoCrop model and a case study with grain sorghum. Agricultural and Forest Meteorology (in press).

Ramírez-Villegas J; Salazar M; Jarvis A; Navarro-Racines C. 2012. A way forward on adaptation to climate change in Colombian agriculture: perspectives towards 2050. Climatic Change. Available at: http://www.springerlink.com/content/u4h33717g7516574/fulltext.pdf

Ranger N; Millner A; Dietz S; Fankhauser S; Lopez A; Ruta G. 2010. Adaptation in the UK: a decision making process. Grantham Research Institute on Climate Change and the Environment/Centre for Climate Change and Policy. http://www2.lse.ac.uk/GranthamInstitute/publications/Policy/docs/pb-ranger-adaptation-uk.pdf

Roudier P; Sultan B; Quirion P; Berg A. 2011. The impact of future climate change on West African crop yields: What does the recent literature say? Global Environmental Change 21(3):1073–1083.

Schafleitner R; Ramírez-Villegas J; Jarvis A; Evers D; Gutierrez R; Scurrah M. 2011. Adaptation of the Potato Crop to Changing Climates. In: Yadav SS; Redden R; Hatfield JL; Lotze-Campen H; Hall A, eds. Crop adaptation to climate change. Wiley-Blackwell, Oxford, UK. p 287–297.

Shah F; Huang J; Cui K; Nie L; Shah T; Chen C; Wang K. 2011. Impact of high-temperature stress on rice plant and its traits related to tolerance. The Journal of Agricultural Science 149(05):545–556.

Sivakumar MVK; Das HP; Brunini O. 2005. Impacts of present and future climate variability and change on agriculture and forestry in the arid and semi-arid tropics. In: Salinger J; Sivakumar MVK; Motha RP. Increasing climate variability and change. Springer, The Netherlands. p 31–72.

Smith LA; Stern N. 2011. Uncertainty in science and its role in climate policy. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 369(1956):4818–4841.

Smith MS; Horrocks L; Harvey A; Hamilton C. 2011. Rethinking adaptation for a 4 °C world. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 369(1934):196–216.

Srivastava A; Naresh Kumar S; Aggarwal PK. 2010. Assessment on vulnerability of sorghum to climate change in India. Agriculture, Ecosystems & Environment 138(3–4):160–169.

Tao F; Zhang Z; Liu J; Yokozawa M. 2009. Modelling the impacts of weather and climate variability on crop productivity over a large area: A new super-ensemble-based probabilistic projection. Agricultural and Forest Meteorology 149(8): 1266–1278.

Taylor KE; Stouffer RJ; Meehl GA. 2012. An overview of CMIP5 and the experiment design. Bulletin of the American Meteorological Society 93(4):485–498. Available at: http://journals.ametsoc.org/doi/pdf/10.1175/BAMS-D-11-00094.1

The World Bank. 2011. Climate-smart agriculture: A call to action. http://www.profor.info/sites/profor.info/files/CSA_Brochure_web_WB.pdf

The World Bank. 2012. World Development Indicators, online database.

Thornton PK; Jones PG; Ericksen PJ; Challinor AJ. 2011. Agriculture and food systems in sub-Saharan Africa in a 4°C+ world. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 369(1934): 117–136.

Tubiello FN; Fischer G. 2007. Reducing climate change impacts on agriculture: Global and regional effects of mitigation, 2000–2080. Technological Forecasting and Social Change 74(7):1030–1056.

UNFCCC (United Nations Framework Convention on Climate Change). 2011. Assessing the costs and benefits of adaptation options: An overview of approaches. Bonn, Germany.

Van den Bergh I; Ramírez-Villegas J; Staver C; Turner D; Jarvis A; Brown D. 2012. Climate Change in the Subtropics: The Impacts of Projected Averages and Variability on Banana Productivity. Acta Horticulturae (ISHS) 928:89–99.

Webster M; Sokolov A; Reilly J; Forest C; Paltsev S; Schlosser A; Wang C; Kicklighter D; Sarofim M; Melillo J; Prinn R; Jacoby H. 2012. Analysis of climate policy targets under uncertainty. Climatic Change 112(3):569–583.

Willows R; Connell R. 2003. Climate adaptation: Risk, uncertainty and decision-making: UKCIP Technical Report. United Kingdom Climate Impacts Programme. Oxford, UK. http://www.ukcip.org.uk/wordpress/wp-content/PDFs/Risk.pdf