Sonia Quiroga *Editor*

Economic Tools and Methods for the Analysis of Global Change Impacts on Agriculture and Food Security

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Contents

Part I Microeconomic Modelling: Risk Management, Adaptation Measures and Stakeholders' Perception

1 Crop Production Functions and Efficiency Models: Climate Change and Water Adaptation Policy Over Competitiveness and Social Disparities of Crop Production in the Mediterranean 3
S. Quiroga, Z. Fernández-Haddad and C. Suárez

2 Using Ecological Modelling Tools to Inform Policy Makers of Potential Changes in Crop Distribution: An Example with Cacao Crops in Latin America 11
Juan Fernandez-Manjarrés

3 The Effects of Climate Change on Poverty and Income Distribution: A Case Study for Rural Mexico 25
A. López-Feldman and José Jorge Mora Rivera

4 The Value of Meteorological Information in Agrarian Producers' Decision Making: Introducing Analytic Decision Models 43
Emilio Cerdá, Sonia Quiroga and Pablo Martinez-Juarez

5 Participatory Process: Approaches for Assessing Farmer Behavior Towards Adopting Climate Change Adaptation Strategies in Sub-Saharan Africa 61
Silvestre García de Jalón

Part II Macroeconomic and Complexity Modelling: Global Challenges and Multi-agent Interactions in Mitigation and Adaptation Policy Analysis

6 CGE Models in Environmental Policy Analysis: A Review and Spanish Case Study 89
M. Bourne and G. Philippidis

7 General Equilibrium Models: A Computable General Equilibrium Model to Analyze the Effects of an Extended Drought on Economic Sectors in México 119
Alejandra Elizondo, María Eugenia Ibarrarán and Roy Boyd

8 Costs and Benefits of Adaptation: "Economic Appraisal of Adaptation Options for the Agriculture Sector" 131
Paul Watkiss and Alistair Hunt

9 The Impacts of Climate Change on Crop Yields in Tanzania: Comparing an Empirical and a Process-Based Model 149
Pedram Rowhani, Navin Ramankutty, William J. Martin, Ana Iglesias, Thomas W. Hertel and Syud A. Ahmed

10 Development of a Prioritization Tool for Climate Change Adaptation Measures in the Forestry Sector—A Nicaraguan Case Study 165
Tania Guillén Bolaños, María Máñez Costa and Udo Nehren

Introduction

Eras of rapid shifts in agriculture have been recorded throughout history. Some of them have been caused by the development of new techniques, tools or species, or simply by shifts in demand patterns. Other disruptive forces have a natural origin, such as large-scale volcano eruptions or non-anthropogenic climate change. Yet the present era is facing a series of changes that will not only affect agriculture but many other aspects of human life. Among them, anthropogenic climate change has attracted great attention. A consensus has been formed over the forecast that greenhouse gas emissions will affect climate patterns at a global level. Some of these changes have already been reported.

Agriculture is, at different levels, sensitive to climate. This implies that most of the expected impacts of climate change will directly affect agriculture and, therefore, food security. Changes in temperatures are probably the impacts most often associated with climate change and would directly affect agriculture, just as potential changes in precipitation patterns particularly. Both impacts would influence water availability and, therefore, agriculture. Precipitation patterns are expected to turn many agricultural areas drier overall but with more concentrated rainfall. Many plant species could be affected by this. Moreover, concentrated rainfall patterns could accelerate soil erosion, also affecting plantations. Temperatures are expected to increase due to the greenhouse effect. This would increase water evaporation, reducing the amount to be collected by plants.

Climate-related extreme events could also affect crops. Events such as floods, draught or frosts can damage crops by directly affecting them and seriously damaging production, or in a more indirect way, such as the aforementioned case of soil erosion caused by flooding events. Yet different regions' agriculture will benefit from climate change. Areas too cold to provide adequate environment to several crops will likely offer an improved context for plant species developed in different geographical contexts. This effect will hardly compensate for the losses caused in agricultural systems in other parts of the world, which could affect sectors highly dependent on agriculture, such as cotton and biofuels. Probably most important, these impacts could have a direct effect over food security. Recent projections estimate that global wheat production could be reduced between a 4.1 and a 6.4% by a temperature increase of 1° (Liu et al. 2016).

Food security, which following definitions used by FAO (2007, 2008), could be associated with the capacity of all members of society which are either able to obtain food on their own means or are able to rely on social networks to ensure their access to adequate food supply, i.e. food able to provide the necessary nutrients for a lifestyle. In 2017, 52 countries were considered to have at least “serious” levels of hunger according to the Global Hunger Index (Von Grebmer et al. 2017). While most of the recent history has witnessed mostly decreasing hunger levels, the situation may worsen if agricultural output is affected by changing climatic conditions in the long term.

Unequal distribution of resources is a matter closely related to both climate change and food security. Research on climate change draws a map where poorer countries could bear the heavier burden of impacts. This has several implications. First, that poorer farmers will suffer more from climate change. Second, that farmers situated in poorer countries will be able to receive social support from their state or communities. Third, that migratory movements might be necessary in order to reallocate farmers no longer able to reach survival rates. Last, and taking into account, that poorer regions are often the most unequal, and it can be deduced that inequalities will grow both within and throughout national borders. Hunger and poverty have an intuitively strong correlation, both at the micro- and macro-levels, though poor individuals in rich countries often have secured an access to food supplies ensured by the state.

The present book addresses these matters by providing a series of tools aimed at improving the capacity of agriculture systems to optimise their performance under meteorological and climatological uncertainties.

Content is structured into two parts: *Microeconomic Modelling: Risk management, Adaptation Measures and Stake-Holders’ Perception and Macroeconomic* and *Complexity Modelling: Global Challenges and Multi-agent Interactions in Mitigation and Adaptation Policy Analysis*.

Part I opens by describing the methodologies carried out in the context of Spain with the aim of studying different policy scenarios’ impacts over production, efficiency and distribution. The second study, Chap. 2, uses species distribution models to assess changes in the Nicaraguan agrarian system. Chapter 3 uses a Ricardian approach to study inequality and poverty in rural Mexico. Next, Chap. 4 describes cost-loss approaches towards valuating weather information in agriculture. Ending this first section, Chap. 5 goes into the topic of participatory approaches developed for Sub-Saharan Africa, in order to analyse behaviour in adaptive strategies.

The first chapter of Part II, Chap. 6, uses computable general equilibrium (CGE) models focused towards policy analysis in Spain. Similarly, the analysis taken in Chap. 7 is based in CGE, which is applied in this case to the study of the impacts that an extended draught could cause in Mexico. Following this, Chap. 8 deals with the potential costs and benefits of adaptation, by describing a series of studies performed at varying scales and depicting their methodologies. Chapter 9 compares two methodologies, statistical and simulation models, studying impacts of climate change over Tanzanian agricultural output. Finally, Chap. 10 addresses the Nicaraguan case in order to design a tool for prioritising efforts in adaptation to climate change.

Sonia Quiroga

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Part I
Microeconomic Modelling: Risk Management, Adaptation Measures and Stakeholders' Perception

Chapter 1
Crop Production Functions and Efficiency Models: Climate Change and Water Adaptation Policy Over Competitiveness and Social Disparities of Crop Production in the Mediterranean

S. Quiroga, Z. Fernández-Haddad and C. Suárez

1.1 Introduction

Worldwide, agriculture represents over 70% of water resource use. Within the sector, irrigation is the process that requires most of this water, therefore, water rights and changes occurring in them play a significant role in sustainability of diverse ecosystems (Bruns and Meinzen-Dick 2000). Efficiency is another reason for concern, as due to inappropriate irrigation schemes, the amount of water being effectively used for plant growth is scarce (Chakravorty and Umetsu 2003; Pan et al. 2003; FAO 2002; Seckler 1996). Spain, as well as other European Union members is affected by these circumstances (Gómez-Limón et al. 2002), with future prospects not being positive, as climate change may add new pressures to agricultural water system's sustainability. It is expected to increase intersectoral conflicts between the agriculture and other sectors, which will lead to reduced water availability for agriculture.

While incentives to increase water efficiency have been under the spotlight as the main tools efficiency by researchers (Gómez-Limón et al. 2002), irrigation rights have been an important instrument used by water authorities. It has been observed that reductions in areas to be irrigated could lead to diminished impacts over crop production in the short term (Liu et al. 2007; Pender and Gebremedhin 2006), particularly for the case of cereals (Quiroga et al. 2011a).

Following the implementation's timetable of the Water Framework Directive (WFD), EU countries will have to implement a series of objectives following two principles: (i) That water consumers (farmers, industries and households) must pay costs of water services; (ii) that assessments made by member states must include

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economic analysis (such as characterization), studying profitability as costs and benefits arising from different strategies. A review of concessions of irrigated land area already in implementation might be considered among policy instruments complying WFD requirements (Atwi and Arrojo 2007; Quiroga et al. 2011a).

EU policies, and in particular the Common Agricultural Policy (CAP) can represent an important influence over irrigated agrarian production. Changes in CAP and the fulfilment of WFD criteria will have to be considered thoroughly by river basin decision makers in the following years. CAP's main aim is to liberalize the agriculture sector and promote its international competitiveness. This objective, though, does not seem compatible with WFD's environmental nature. The MacSharry reform (1992) of the CAP introduced a direct payment scheme for the 1993–99 period, and prolonged throughout 2000–04 by Agenda 2000.

The methodology follows that used in Quiroga et al. (2014), which applied it in order to obtain results for the most relevant crops in the region of the Ebro basin in Spain. This methodology proposed in this chapter is focused on the study of policy scenarios in contexts of changing irrigated lands' distribution. The study followed several steps: (i) On the one hand agricultural systems' changes in efficiency are considered. In order to perform this analysis, the stochastic production function was calculated (in the form of a Cob Douglas function). The resulting production functions and specifications for technical efficiency varied depending not only on socioeconomic and biophysical factors, but also on their interactions. Values for each crop were calculated specifically in order to make it possible to determine the implications of technical efficiency over water management. (ii) On the other hand, distributional aspects were studied through the analysis of the marginal effect of irrigated area over inequalities in crop yields through a decomposition of the Gini index. Measuring technical efficiency and distribution of agrarian output offers new information on competitiveness and distribution of crops in the region and allows for a potential increase in productivity and its social impacts.

1.2 The Stochastic Frontier Production Function

The agent optimizing behaviour assumption underlies the theoretical structure of the study, even though solving the optimization problem is not always a possibility for producers or consumers. Still, vital for the study is the analysis of deviations from the technical and/or economic frontier. These deviations give a measure of technical inefficiencies. The Stochastic Frontier Analysis (SFA) is used in order to compute these distances. This technique allows for the capture od data noise and the inclusion in the production function of climate-related variables, which should increase the accuracy of the measurements. SFA has also limitations, namely, possible misspecification problems (Hoang and Coell 2011). The methodology here described allows for the study of changes in crop efficiency over time but was not used in order to tackle the question of whether crops are more efficient from the technical perspective in some areas and less efficient in others.

Cobb-Douglas functions were chosen due to their simplicity and their general capability of describing production (Zellner et al. 1966, Giannakas et al. 2003), and due to the fact that they performed better than trans-log functions for the research performed. Neutral technological progress was used in the Cobb-Douglas stochastic frontiers. Technical efficiency effects are modelled for the study region (in the case study referenced the five provinces of the Ebro basin) for the studied crops for unbalanced panel data (Battese and Broca 1997; Battese and Coelli 1995; Huang and Liu 1994). Predicted technical efficiency levels are also included alongside estimates of the production elasticities with respect to the inputs considered for all crops studied. Technical efficiency measures carry constitute important sources of information, as their role is thoroughly studied in order to obtain information vital for both public policy and private farm-level decision-making. These technical efficiency effects and their distribution along the study area are estimated through production functions.

The models proposed by Battese and Coelli (1995) and Huang and Liu (1994) are used in order to estimate inefficiency levels of economic agents and are also to be used in order to define their inefficiency according to different explanatory variables.

$$Y_{it} = \exp(f(x_{it}, \beta) + V_{it} - U_{it}); i = 1, \ldots, N, t = 1, \ldots, T \quad (1.1)$$

$\boldsymbol{Y_{it}}$ refers to the logarithm of the production of firm i in period t.$\boldsymbol{f(x_{it}, \beta)}$ represents a given function of the kx1 vector of (transformations of) x_{it} inputs in farm K for period t; while β is a vector of parameters to be estimated. V_{it} is a random parameter vector which encapsulates statistical noise in outputs, *iid*, $\left(\boldsymbol{V_{it}} \sim^{iid} \boldsymbol{N}\left(0, \boldsymbol{\sigma_v^2}\right)\right)$ and independent of U_{it} with U_i as a random variable representing technical inefficiency in production and as *iid* is truncated at 0, $\left(\boldsymbol{U_i} \sim^{iid} \boldsymbol{N^+}\left(z_{it}\boldsymbol{\delta}, \boldsymbol{\sigma_u^2}\right)\right)$.

The general model proposed in the study takes the form of:

$$\ln Y_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j \ln x_{jit} \beta_{it} t + V_{it} - U_{it} \quad (1.2)$$

The Cobb-Douglas formulation taken is often used in such studies. t is a variable added in order to obtain a measure of Hicks-neutral technical change. Technical inefficiency is defined, following these models, as:

$$U_{it} = z_{pit}\delta + W_{it} = \delta_0 + \sum_{n=1}^{N} \delta_p z_{pit} + \delta_{it} t + W_{it} \quad (1.3)$$

With z_{pit} representing a *1xm* vector containing technical inefficiency explanatory variables for farm i. δ is an *mx1* vector with unknown coefficients. Technical efficiency is defined as $\boldsymbol{TE_{it}} = \mathbf{exp}_{it}(-\boldsymbol{U_{it}}) = \mathbf{exp}\left(-\left(\boldsymbol{\delta} + \sum_{p=1}^{J} \boldsymbol{\delta_p z_{pit}} + \boldsymbol{\delta_{it} t} + \boldsymbol{W_{it}}\right)\right)$. Conditional expectations of individual “agents” are used to calculate efficiencies of these agents taking into account the assumptions made by the model: $\boldsymbol{TE_{it}} = \boldsymbol{E}\left[\mathbf{exp}(-\boldsymbol{u_{it}} | \boldsymbol{\varepsilon_{it}})\right]$. Technical efficiency with respect to the production frontier can be written as $\boldsymbol{TE_i} = \boldsymbol{E}\left(\boldsymbol{Y_i^*} | \boldsymbol{U_i}, \boldsymbol{X_i}\right) / \boldsymbol{E}\left(\boldsymbol{Y_i^*} | \boldsymbol{U} = 0, \boldsymbol{X_i}\right)$ for year $\boldsymbol{t}$.

The estimation of parameters was performed through the Maximum-Likelihood (ML) method. This methodology models temporal variation of technical inefficiency by using the error component instead of the intercept of the production frontier. This ML approach requires strong assumptions about the distribution of errors U_i: semi-normal and truncated normal (Battese and Coelli 1988, 1992, 1995; Kumbhakar 1990; Cuesta 2000, among others). ML method is used for the joint estimation of the parameters of the stochastic frontier as well as for the model for the technical inefficiency effects. The likelihood function has been formulated in terms of the variance parameters (Battese and Coelli 1993). The parametrization of Battese and Corra (1977) is used, taking into account the calculation of maximum likelihood estimates, as $\boldsymbol{\sigma}_V^2$ and $\boldsymbol{\sigma}_U^2$ are replaced by $\boldsymbol{\sigma}^2 = \boldsymbol{\sigma}_V^2 + \boldsymbol{\sigma}_U^2$ **and** $\boldsymbol{\gamma} = \boldsymbol{\sigma}_U^2/\boldsymbol{\sigma}_V^2 + \boldsymbol{\sigma}_V^2$. Parameter γ belongs to the interval between 0 and 1, with an initial value that can be extracted by using an iterative maximization process (Coelli et al. 1998).

The null hypothesis, $\boldsymbol{H}_0 : \boldsymbol{\gamma} = 0$, indicating that returns-to-scale technology is constant is tested, which would imply no technical inefficiency. A second null hypothesis to be tested, $\boldsymbol{H}_0 : \boldsymbol{\delta}_i = 0$, is related to the lack of technical inefficiency effects. Within the technical efficiency model, marginal effects for every variable z can be calculated as

$$\frac{\partial \boldsymbol{TE}_{it}}{\delta z_{pit}} = \frac{(\partial \boldsymbol{E}\mathbf{exp}(-\boldsymbol{U})|\boldsymbol{\varepsilon}_{it}]}{\partial z_{pit}} = \boldsymbol{TE}_{it}\boldsymbol{\Psi}\partial_p \tag{1.4}$$

With: $\boldsymbol{\varepsilon}_{it} = \boldsymbol{V}_{it} - \boldsymbol{U}_{it}$ and

$$\boldsymbol{\Psi} = \frac{1}{\boldsymbol{\sigma}_w}\left[\boldsymbol{\sigma}_w + \frac{\phi(\boldsymbol{\rho})}{1-\boldsymbol{\Phi}(\boldsymbol{\rho})} - \frac{\phi(\boldsymbol{\sigma}_w+\boldsymbol{\rho})}{1-\boldsymbol{\Phi}(\boldsymbol{\sigma}_w+\boldsymbol{\rho})}\right] \text{ and } \boldsymbol{\rho} = \frac{1}{\boldsymbol{\sigma}_w}\left[\delta_0 + \sum_{p=1}^{J}\delta_p z_{pit}\right]$$

where ϕ and Φ are density and distribution functions respectively of the standard normal random variable (Zhu et al. 2008).

1.3 Decomposition of the Gini Coefficient

Gini coefficients are used in this case to add the inequality component to the analysis carried out. This coefficient is used extensively and is the most common index tackling inequality due to its simplicity and properties. Though it has been applied in diverse fields, its uses in environmental and agricultural economics has been less common (Sadras and Bongiovanni 2004; López-Feldman et al. 2007; Seekell et al. 2011).

This inequality index is characterized following the works by Pyatt et al. (1980) and Shorrocks (1982), and extended by Lerman and Yitzhaki (1985), therefore including the marginal impact of different aspects on inequality of overall yields, paying special attention over the impact of water related variables.

The Gini coefficient can take values between zero (distribution is equal) to one (an agent accumulates the whole, perfect inequality). It fulfils properties of population size independence, symmetry, and Pigou Dalton transfer sensitivity Haughton and Khandker 2009). In contrast, the index also has two significant drawbacks. First, a difficult decomposability as entropy measures; second, a complex statistical testability for significance of index changes over time, though it has been speculated that this is not a real trouble due to the possibility of using confidence intervals through the help of bootstrapping techniques (Haughton and Khandker 2009).

The approach employed for this methodology is the mentioned Gini decomposition, which develops how the product of each source's share on total output can be used in order to observe its contribution to the general coefficient. Its correlation with the total output and can be expressed as:

$$G_{tot} = \sum_{k=1}^{K} S_k G_k R_k \tag{1.5}$$

With G_{tot} showing the Gini coefficient of the total yield; S_k representing the share of k in that total yield. The higher this value, the higher the importance of source k on the yield. G_k refers to the relative Gini coefficient of source k, which seeks to determine the equality or lack of it in the income source. R_k represents the correlation of source k and total yields in terms of their Gini coefficients. $\boldsymbol{R_K} = \mathrm{cov}\{\boldsymbol{y_k F}(\boldsymbol{y})\}\mathrm{cov}\{\boldsymbol{y_k F}(\boldsymbol{y_k})\}$ which brings up the question of where the correlation between income source and the distribution of total income lies. The decomposition employed eases the understanding of the determinants of inequality, allowing to the estimation of impacts caused by small changes in a source of yield over inequality, *caeteris paribus*.

$$\frac{\partial G_{tot}}{\partial e} = S_k (G_k R_k - G_{tot}) \tag{1.6}$$

1.4 Case Study: Ebro Basin in Spain

The study presented, Quiroga et al. (2014), obtained results for the case of the Ebro basin following, as previously mentioned, the methodological steps here presented. These results are cantered in two crops: maize and grapevine; and the reference period spanned from 1980 to 2002. Crop yield (Yit) at farm I during year t, was taken as dependent variable. Other relevant variables could be classified between socio economic and biophysical factors.

- Socio-economic factors: Number of epmloyees at the agricultural sector at a site i in year t (Lit), a technology indicator (Techit), total area irrigated for each crop type (Irrig_areait), and net water needs per year (Irrigit), Human Development Index at a site (as a percentage of the total for the country) (HDIit), dummy variables referring

Table 1.1 Cobb-Douglas crop production functions and technical efficiency models

Cobb-Douglas crop production function			Technical ineficiency = U		
Variables	Maize	Grapevine	Variables	Maize	Grapevine
Tech	0.0339*** [0.009]	0.0353** [0.015]	Altitude(0-600)		0.0014*** [0.000]
ln(L)		−0.5144*** [0.086]	Altitude(601-1000)		-0.0017*** [0.000]
Cent_Ebro	−0.1896*** [0.050]	−0.3456*** [0.091]	Altitude(+1000)	0.0001** [0.000]	0.0009*** [0.000]
Northern_Ebro	−0.2526*** [0.057]	−0.5174*** [0.158]	Irrig_area	−0.0272*** [0.005]	−0.1178*** [0.031]
ln(Irrig)	0.0516*** [0.013]		HDI	−0.1387** [0.064]	0.9901** [0.387]
ln(Irrig_area)	0.0263** [0.012]	0.0604*** [0.014]	MacSharry	−0.8192** [0.352]	0.506 [0.752]
ln(Precyear)	0.0133 [0.032]	0.3331*** [0.060]	Agenda2000	1.1422*** [0.401]	1.5419** [0.758]
ln(T_Meanyear)	−0.5656*** [0.160]	1.8381*** [0.391]	Year		−0.4427** [0.186]
Drought		−0.1221** [0.061]	Constant	12.5577** [5.806]	−89.7326*** [33.055]
Constant	3.0243*** [0.509]	−4.1888*** [1.257]			
Observations	268	193			

Standard errors in brackets. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. *Source* Quiroga et al. (2014)

to the two PAC reforms deemed as relevant for the matter of study—MacSharry Reform in 1994 (MacSharryt) and Agenda 2000 in 2001 (Agenda 2000t)—and the time trend (t = 1 for 1976, t = 27 for 2002) (T).

- Bio-physical factors: Classification of total area in km^2 accordint to the altitude zone (0–600, 601–1000 and >1000 m of altitude) (Altitudei), The 3 main areas of the basin (Northern, Central and Low Ebro) were classified through dummy variables (Area_ebroi), yearly precipitation levels at a site (Precit), average annual temperature at a site in the (T_Meanit) and a dummy variable which differencuated drought years (1 for drought years, 0 in other cases) (Droit).

Table 1.1, extracted from Quiroga et al. (2014), summarizes the results of the regression performed in the study. It can be seen that irrigation has a positive impact over maize crop yields, which means that lower availability of water would diminish production. In the case of grapevines, it is the variable drought that has a significant impact over its yield.

The table also shows factors explaining changes in the technical inefficiency model, though signs have opposite implications over productivity, i.e. a negative sing in the estimates implies that the variable's effect over efficiency is positive. It can be extrapolated that irrigated area has therefore a positive impact over technical efficiency in both maize and grapevine.

1.5 Discussion and Conclusions

Changing socioeconomic and climatic contexts will probably increase significantly pressures over water systems and therefore over the agrarian sector; which will be related to an increase in water conflicts caused by climate change. The analysis of these changes requires a comprehensive view that includes impacts over long-term efficiency levels and income distribution. This methodology could help to evaluate the impacts of changes in irrigation duties on efficiency levels and distribution of agricultural productions, extrapolating the case study performed in the Ebro river Basin to other geographical areas and crop types. The use of this methodology can also be extended in order to study topics such as impacts of the modernization process over irrigation systems, fertilizer use or agricultural subsidies.

The results of the case study showed positive impacts of irrigated areas, which had stabilizing effects over the distribution of production, due to higher impacts over less favored socioeconomic groups. Moreover, positive impacts of irrigated areas over technical efficiency were observed. A consequent policy recommendation would point towards the avoidance of reducing irrigated areas, on the basis that such policies could impact socioeconomic variables in a negative manner.

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Chapter 2
Using Ecological Modelling Tools to Inform Policy Makers of Potential Changes in Crop Distribution: An Example with Cacao Crops in Latin America

Juan Fernandez-Manjarrés

2.1 Introduction

One consequence of climate change that is becoming increasingly clear, is the shift in species distribution of certain wild species because of climate change (Parmesan 2006). However, assigning climate effects to distributional shifts has not always been straightforward because of other factors. For instance, changes in land use can produce new empty ecological niches[1] and habitats[2] that are used by local or alien species (Parmesan and Hanley 2015). Likewise, economists, agroecologists and enterprises ask themselves if the current distribution of crops would change with ongoing climate change, and if yes, to what extent. Clearly, if the climate related to crops is no longer suitable, the economic and social costs of replacing crops, or of changing cultivated areas is extremely large, so early awareness of what might happen is needed for policy makers.

To simulate the potential shifts in the distribution of species, ecologists have been using for the last 15 years or so the so called '*species distribution models*' (hereafter **SDM**) or '*niche models*'. As we will see in the following sections, SDM are statistical models that correlate the observed presence of a species (or crop for that matter) with climatic and geographic features of the zones for which occurrences of the species in question are known. They are not mechanistic models, but correlational models built upon a series of assumptions. These models have attracted the researchers in

[1] The definition of niche is characterized by the ecological role of a species in a natural community, but is also used in a more loose form to refer to the microhabitat or the physical space occupied by a species. In this chapter, we retain the latter use.

[2] Habitat is the locality, site and particular environment occupied by an organism and as such the definition overlaps that of niche in terms of spatial occupation. For coherence with the models, we will use only niche in this text.

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ecology, because they are less data intensive than mechanistic models (i.e., models based on photosynthesis and mineral exchanges with the air and the soil) and are easy to spatialize.

These models are extensively used not only for endangered species but for managed forests, pests and invasive species as we will see later in the text. Crops, on the other hand, have used somewhat different statistical models based mostly on matching the current requirements of a crop with its climate, but to some extent, models in ecology and agronomy may have to start to converge in the same family of modelling tools.

The world distribution of crops has been traditionally understood as zones delimited by extremes of temperature and precipitation (Kottek et al. 2006) while the changes of crop productivity and distribution has been modelled with several types of models (see Holzkämper 2017 and references therein). They include empirical, suitability, biophysical, meta- and decision making models.

In this chapter, we will discuss the use of SDM in crop science, that is a type of suitability model *sensu* Holzkämper (2017). The approach might be perceived as biased, but as we will see, it may be flexible enough to forecast potential shifts not only in crops, but in their related pests and diseases as well as invasive species, all of which have economic impacts with relatively small quantities of data.

We will first review briefly the literature on SDM and crops. Second, we present the general background of the models and introduce MaxEnt (Phillips et al. 2006; Phillips and Dudik 2008), that has emerged as very robust modelling platform based on maximum entropy theory models. We then present an application for crops zones in Latin America where both coffee and cacao are planted, as these zones are very likely to be affected by climate change, with impacts on two very independent value chains. We finish by discussing the limits of the approach and with a word of caution regarding the mis-use of this kind of models.

2.2 Current Use of Species Distribution Models

Overall, the use of SDM models is relatively recent. The oldest reference in our search examines the potential conflict of geese and crops (Jensen et al. 2008) just about 10 years ago at the time of publishing. As said in the introduction, the question of crop distribution and climate has been treated for a long time, but it is the use of SDM that appear as a cost-efficient alternative for researchers and managers.

This first generation of use of SDM in agriculture has led to a majority of articles on staple foods likes corn, wheat and rice, but also on diseases, invasive species, pests and pollinator distribution under current and climate change conditions. A search on "SPECIES DISTRIBUTION MODELS") *AND* **TOPIC**: (CROPS) in Web of Science® in early 2018 provided 75 records from which only four were review papers (Fig. 2.1).

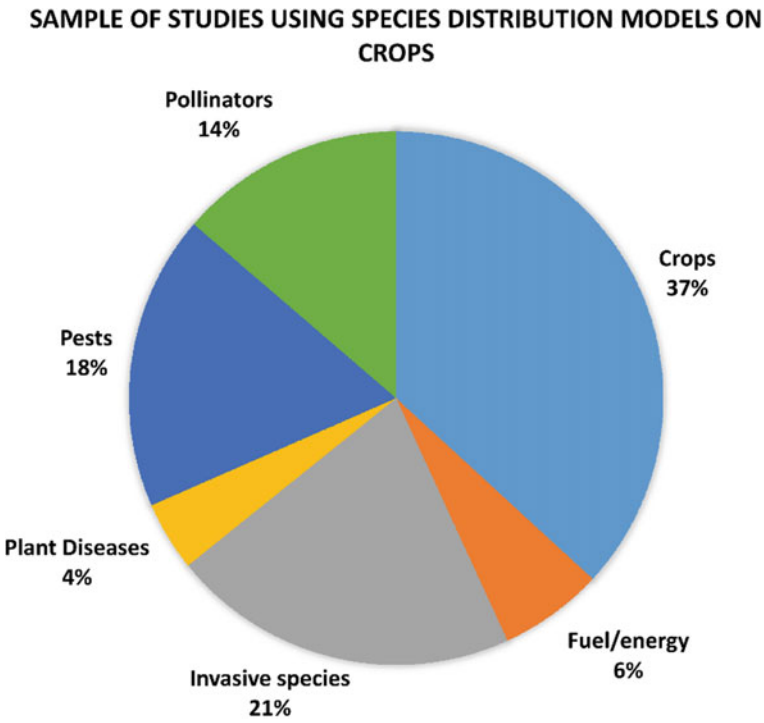

Fig. 2.1 Proportion of articles that use species distribution models for crop science studies. See text for details

As we will see in the next section, the power (and weaknesses) of SDM resides in the use of geo-localized data to infer current suitable habitat that is easily transposable to future conditions if climate change projections are available. The fact that known localities are used as the main input, makes SDM highly applicable to different types of organisms (vertebrates, insects, nematodes, etc.) and for crops that are thought to be cultivated within their normal biological niche.

2.3 Species Distribution Models: Maximum Entropy Models

An intuitive relation between climate, soil, altitude and the distribution of animals and plants is probably one of the oldest ecological observations that human kind has made. However, what appears so self-evident and intuitive has proved enormously difficult to formalize correctly in statistical terms. As it is well known, correlational methods can adequately model and predict on models calibrated *on what is seen* (observed localities) but cannot make inferences *about what is not seen* (unknown parts of the distribution) without making assumptions and simplifications.

Earlier SDM models used an empirical approach for calculating a climatic 'envelope' for a given species based on the known occurrences. But this kind of model very soon attained their limits because (a) it is frequently unknown if the current distribution of a species represent the complete physical and climatic space that a species can survive and reproduce; and (b) the more variables used, the more difficult to generalize the distribution to unknown parts as almost everywhere the variable combinations are unique, so they are not transposable in space and time. Hence, several statistical methods emerged to allow for a probabilistic approach to the problem. From about a dozen that appeared in the early 2000s, the maximum entropy approach (hereafter MaxEnt) by Phillips and collaborators (Phillips et al. 2006, 2018; Phillips and Dudik 2008) appeared particularly robust but not completely exempt of controversy about the assumptions and meaning of the output. MaxEnt methods have been used in more than 7000 peer-reviewed studies at the time of writing and its popularity seems to continue. Interestingly, recent generalizations of the species distribution problem is showing that many different competing methods can be related through an alternative approach of not modelling the probability of presence but by modelling the probability of a point observation in a given space (Renner et al. 2015).

Before explaining the procedure, let us first formalize the input data and the goal of the simulation. Frequently, when discussing SDM, two families of models are mentioned, those based on *presence/absence* data, and those *presence only* data. MaxEnt belongs to the second category but the notion of absence is necessary in the formalization of the model. The general idea of using maximum entropy methods is explained by Phillips et al. (2006) in his original paper:

> The idea of MaxEnt is to estimate a target probability distribution by finding the probability distribution of maximum entropy (i.e., that is most spread out, or closest to uniform), subject to a set of constraints that represent our incomplete information about the target distribution.

The idea of maximum entropy approaches imply that the goal is to find the *most spread out* distribution based on what is known from the data, i.e., a maximum entropy distribution. Next, I summarize the statistical description given by (Elith et al. 2011) skipping many details for the sake of brevity. The approach assumes that the data available are a set of locations within a landscape of interest L. Next, the presence of the focus species needs to be coded in binary form: $y = 1$ denote presence, $y = 0$ denote absence. Associated to the presence points, there is a need to define a vector of environmental covariates (mean annual temperature, summer precipitation, drought index, altitude, soil type…) which is called z. Finally, there is a need to define a '*background'* in which the z vectors occur, that is defined as a random sample of locations within the landscape (Elith et al. 2011). The environmental covariates z are available for the whole landscape as is the case for example with climate or elevation layers from geographic information systems that are found in pixel form.

The next step is to define independent probability distribution related to the covariates in the landscape, for the occurrences and for the absences. Hence, $f(z)$ defines the probability density of covariates across the landscape, $f_1(\mathrm{z})$ the probability density of covariates for the locations where the species is present, and $f_0(z)$ where the species is absent. It follows then that the quantity to be estimated when presence-absence data is available, is the *probability of presence of the species*, conditioned on the environment:

$$\Pr(y = 1|z).$$

Presence-only data only allow only to estimate $f_1(z)$, which cannot be used to estimate the probability of presence, because it is assumed that not *all* localities are known for the focus species. However, presence/background data allow to model both $f_1(z)$ and $f(z)$ if we knew how the two relate them through a constant C using Bayes' rule:

$$\Pr(y = 1|z) = f_1(z) * C/f(z)$$

It turns out that the needed constant $C = \Pr(y = 1)$, corresponds to the 'prevalence of the species' (or the proportion of occupied sites) in the landscape. So the challenge is to estimate $\Pr(y = 1)$, of course. In entropy terms, the probability of the distribution of the covariates across the landscape $f_1(z)$, can be found through the Gibbs distribution exponential form (Elith et al. 2011):

$$f_1(z) = f(z)e^{\eta(z)}$$

$$\text{where } \eta(z) = \alpha + \beta * h(z)$$

and α is a normalizing constant that ensures that $f_1(z)$ sums to 1, β is vector of coefficients applied to the different terms of model, and $h(z)$ is the vector of constrained features. Hence, the target of a MaxEnt model is the exponential term that estimates the ratio $f_1(z)/f(z)$.

As there is no analytical solution, the parameters are estimated by regression methods and machine learning techniques. The lack of explicit absence observations (museum samples only record presence, for example) is worked around by using random-pseudo absences during the regression iterations. Typically of machine learning techniques, MaxEnt sets aside a portion of the data to train the model and the rest to test the model.

MaxEnt transforms the original covariates (environmental information) in polynomials and splines, including piecewise linear functions data that are termed 'features' to allow for the complex response of organisms to climate and other biotic data. Restrictions to the features are needed to avoid the overfitting of the models. For a detailed description of the analytical development, the reader is directed to the work of Phillips and colleagues (Phillips et al. 2006, 2018; Phillips and Dudik 2008; Elith et al. 2006, 2011).

In its current version[3] 3.41, MaxEnt produces several types of outputs, including tests to evaluate the overall robustness of the model and for identifying which variables are more important. The raw output of MaxEnt represents a probability of *suitable* conditions issued directly from the exponential model above that are extremely low. However, the recommended output is a complementary log-log (*cloglog*) transform that is most appropriate for estimating a measure of abundance—the number of presence records per unit area (Phillips et al. 2018; Renner et al. 2015; Fithian et al. 2015) than probability of presence that is riddled with several theoretical and practical issues.

2.4 Potential Changes of Cocoa and Coffee Plantation Zones in Latin America

We will show briefly an example of the application of MaxEnt procedures to a crop distribution that can be of great interest to economists and policy makers. Cocoa (*Theobroma* spp.) and coffee (*Coffea arabica*, *C. robusta*) are two staple products in Latin America. In general, they do not occupy the same ecological zones. This localities where found from an internet and library search of co-occurrences of coffee and cacao plantations using the Spanish and Portuguese languages (C. Castañeda, unpublished report). We focused on these transition areas (Fig. 2.2) as climate change is opening new areas for the culture of cacao, that are often in zones where coffee plantations are decreasing their productivity because of warmer climates, droughts and emerging pests (Quiroga et al. 2015).

The input data for MaxEnt is then composed of the latitude/longitude of the localities plus the different environmental variables (Table 2.1) chosen to explain the distribution of the species (crops in this case).

The most common source of downscaled environmental and climatic files is the Worldclim organization[4]. The variables typically used in the ecological field are the so called bio-climatic variables[5] because they have been shown to represent mean conditions and more importantly, limiting factors for many plant and animals. In our case we selected the following variables: BIO1 = Annual Mean Temperature, BIO4 = Temperature Seasonality (standard deviation *100 for temperatures and BIO12 = Annual Precipitation, BIO15 = Precipitation Seasonality (Coefficient of Variation) for precipitation. Typically, about a dozen or so climatic variables are used, but here we chose just to use only mean annual values and intra-annual measures of variability for illustration purposes.

Particular efforts must be done to ensure that the localities are not auto-correlated or artificially clustered around roads or research centres, which is often the case. Also, the use of several climate variables may be unnecessary and even counterpro-

[3]https://biodiversityinformatics.amnh.org/open_source/maxent/.

[4]http://www.worldclim.org/.

[5]http://www.worldclim.org/bioclim.

Table 2.1 First ten records of the MaxEnt input file

Species	Longitude	Latitude	Altitude	BIO1	BIO4	BIO12	BIO15	Soil
Cacao_coffee	−92.349306	15.0721667	296	26.5	717	3799	81	30
Cacao_coffee	−92.336806	15.0790833	296	26.5	717	3799	81	30
Cacao_coffee	−83.68005	9.90670556	793	22.1	642	2811	31	16
Cacao_coffee	−72.916667	−12.3	755	24.5	593	1715	50	1
Cacao_coffee	−74.289722	−13.366667	3825	8.7	989	879	81	6
Cacao_coffee	−75.997858	−9.2957639	829	23.7	294	2580	40	13
Cacao_coffee	−72	−11.25	543	24.8	606	2071	47	13
Cacao_coffee	−74	−13.5	4126	6.8	1005	818	80	1
Cacao_coffee	−76.557147	3.12835833	979	23.8	298	1989	35	20
Cacao_coffee	−76.229028	3.25152778	1107	23.7	272	1461	42	13

The first column is the name of the species in question, the second and third column are the geographic coordinates and the fourth column is the altitude in meters. The columns marked as *bio_* represent bioclimatic variables, and the last column is soil data (http://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/). See text for additional details

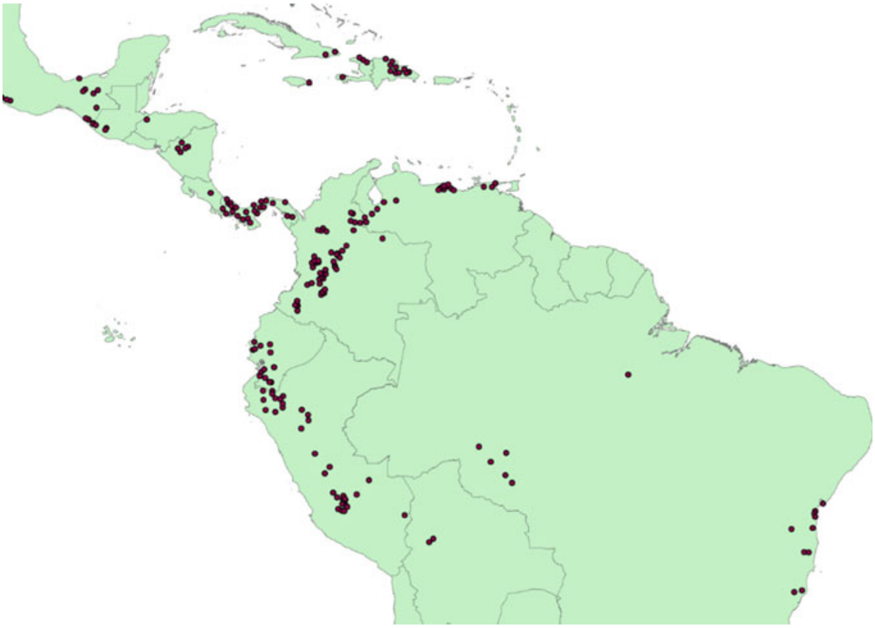

Fig. 2.2 Transition zones between coffee and cocoa plantation localities in Latin America use to run the species distribution model ($n = 199$)

ductive because of over-fit of the models, but more importantly because of correlation between variables. A first screening of pairwise variable correlation is common practice to avoid duplicate entries that can overfit models and that also obscure the interpretation of results. However, some correlation in the climate data is always present and there are no current recommendations of how to deal with this.

To produce an output in graphic form, MaxEnt requires that the user provides a directory with each one of the layers included in the input data table, i.e., from altitude, bioclimatic variables and soil types for current conditions. If the distribution model is intended also for a simulation under climate change for example, the same equivalent files area needed for the period in question as we will see later in the text. MaxEnt will produce maps for current and expected distributions that can be used as input for other analyses.

The command line to run the model in our case was:

> "java density.MaxEnt nowarnings noprefixes -E" " -E cacao_coffee responsecurves jackknife "outputdirectory=F:\Maxent Cacao\current_out" "samplesfile=F:\Maxent Cacao\maxent_cacaocoffee.csv" "environmentallayers=F:\Maxent Cacao\current" replicates=10 -t soil"

but the program has an interface that does not require command line commands. Note that the program is instructed to use the specific sample file "*maxent_cacaocoffee.csv*" (Table 2.1), produce response curves for the different

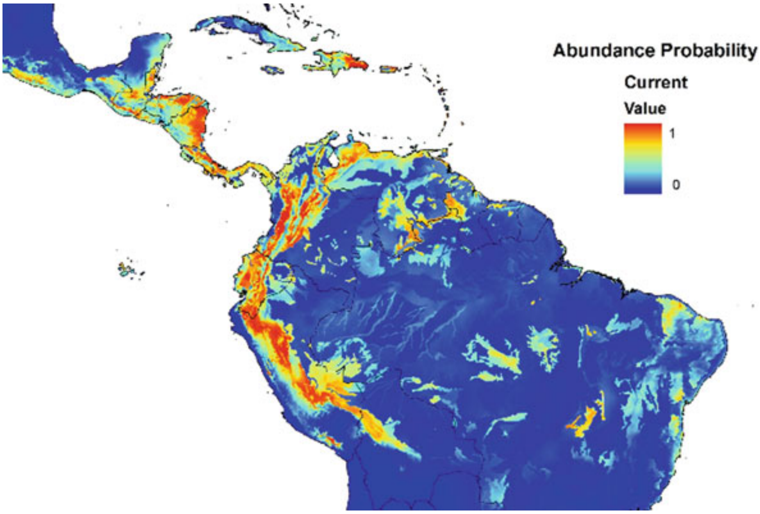

Fig. 2.3 Output for the probability of abundance from the maximum entropy model for a reference climate derived from 1970–2000 observations. See text for details

variables and to jackknife the data to have replicates of training/test runs. In the case of a climate change simulation, an additional "projection layers" instruction is needed as well as an additional output directory for the projection. Finally, it is specified that 'soil' is not a continuous variable but a discrete one indicated by '$-t$' (Fig. 2.3).

Typically, more than one climate change model will be used, not only for each frame time, but from each representative concentration pathways (*rcp*) as currently defined in the fifth IPCC report.[6] Here we present only one simulation (Fig. 2.4) for the rcp 6.0 and the IPSL global circulation model.[7]

The most popular statistic for examining the robustness of a SDM is the AUC or area under the receiver operating characteristic (ROC) curve that remains controversial (Jiménez-Valverde 2012). This index depends on the use of thresholds that remain themselves a matter of research (Liu et al. 2016). In general the presence threshold is varied from 0 to 1 to be able to compute how many false positives and false negatives you get at each level. Figure 2.5 shows the MaxEnt output

The cocoa/coffee was split into two partitions, 75% for training and 25% for testing during 10 different runs (cross-validation). The red (training) line shows the "fit" of the model to the training data while the blue (testing) line indicates the fit of the model to the testing data, corresponding to the predictive power of the model. The black diagonal line depicts a model no better than random (Fig. 2.5).

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[6]http://www.ipcc-data.org/guidelines/pages/glossary/glossary_r.html.

[7]http://ocmip5.ipsl.fr/models_description/ipsl_ipsl-cm4.html.

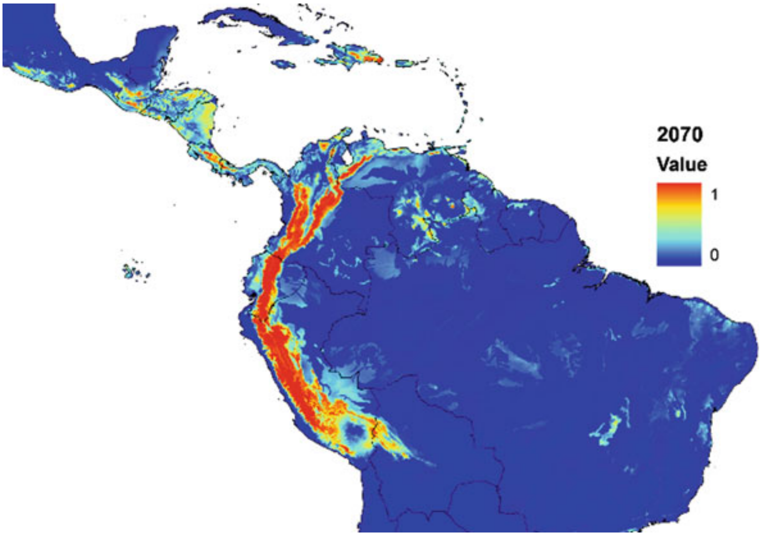

Fig. 2.4 Output for the probability of abundance from the maximum entropy model for the projection in 2070 of the model fitted on 1970–2000 climate (Fig. 2.3)

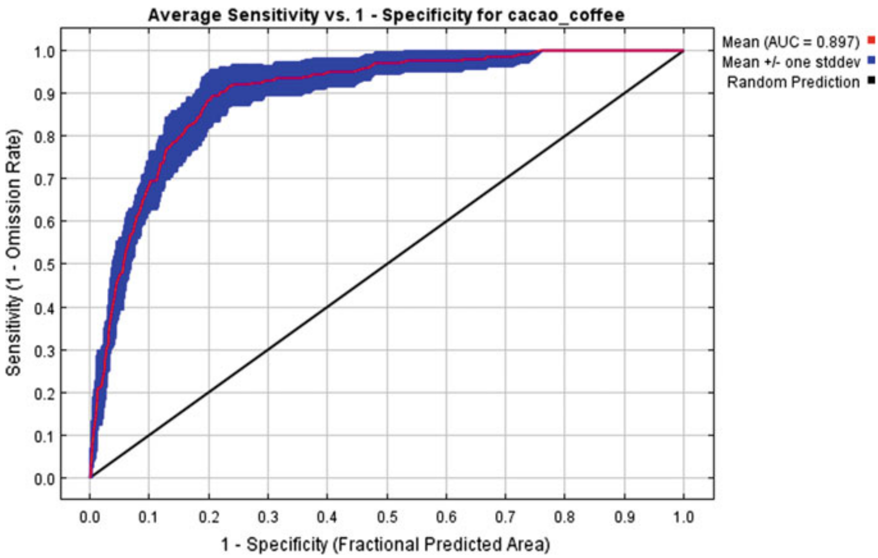

Fig. 2.5 Average sensitivity (true positive rate of simulated locations) against false positive rate (1—Specificity). Sensitivity is the probability that a model correctly classifies a presence. Specificity is the probability a model correctly classify an absence. The average AUC for this model is 0.897

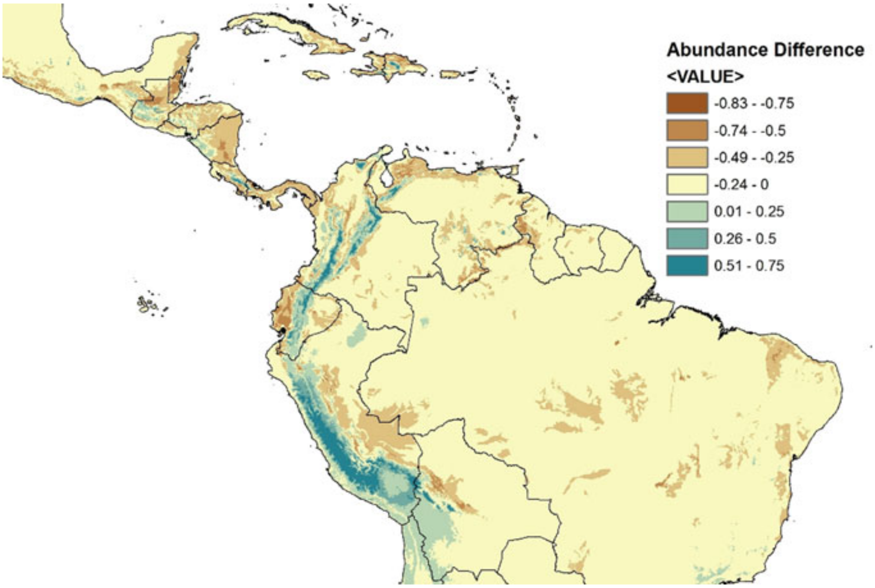

Fig. 2.6 Differences in expected abundance between a baseline scenario (1970–2000) and 2070 (Figs. 2.3 and 2.4). Light green-blue areas represent zones for which the two cultures will potentially increase their abundance as a result of shifting climatic conditions; yellow and the different shades of brown represent zones where potentially the conditions for 2070 will reduce the abundance of the two crops

For what kind of application can these distributions be used in the economic sciences? In general terms, the SDM predict suitable areas for a species or for a crop if the known distribution covers enough of the climate niche of the species or crop. Hence, one straightforward analysis would be to subtract the future suitability from the current suitability to examine which areas will lose suitability and which will gain. Such information could be easily translated into economic models (but see last section) and help managers and decision makers (Fig. 2.6). Clearly, the lowlands show a deterioration of climatic conditions and the Andean region seems to be the most suitable for cacao and coffee plantations for the conditions predicted with this model for 2070. Likewise, one could do the same exercise regarding coffee/cocoa pests and diseases to further refine this analysis if the data were available.

2.5 A Word of Caution

We have seen that with relatively few records ($n = 199$) we are able to produce more than decent suitability maps for the crops in question as their AUC was quite five (~0.90). All this with relative low computer power and using available downscaled climate change models. However, several points must be mentioned first before it is recommended to use this kind of models:

- SDM models produce better predictions near the real observations. Predictions outside of these areas have large uncertainty. MaxEnt provides various analysis to verify this, and they should be taken seriously.
- The biggest danger is probably due to the fact that a modest number of observation produce decent models and always a very appealing map can be produced. The more data, the better (but see next).
- Data need to be trimmed as auto-correlated data, like excess of collection around research stations biased the models. Remember the models assume a random sample of the presence of the species
- The use of several auto-correlated climate layers can improve the AUC of an otherwise mediocre model.
- The use of statistically downscaled climate layers for future conditions is subject to debate. The output of global circulation models is quite coarse (typically 5 degrees or so) and statistical downscaling might be considered an artefact to get high resolution maps.
- For many invasive species with short life cycles, it has been shown that their original climatic niche does not correspond to their climatic niche when they invade new areas as evolutionary adaptation can occur very rapidly in some organisms. Thus, SDM may underestimate the invasive potential of a species.
- And last, but not least, SDM should be used to generate hypothesis of what might happen and not to anticipate events.

2.6 Summary

Species distribution models (SDM) is a powerful simulation tool that has become widely used in the ecological and agronomical sciences. The use of easily available presence data, global downscaled climate layers and software that can run on desktop computer has contributed to their popularity. The most used application is based on maximum entropy models that fit presence data to a series of environmental descriptors. SDM can be used to predict crop distribution under future conditions but the level of uncertainty of those models can be very high. The best use of these models is to be used as generators of hypothesis to be combined with other type of analysis.

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Chapter 3
The Effects of Climate Change on Poverty and Income Distribution: A Case Study for Rural Mexico

A. López-Feldman and José Jorge Mora Rivera

3.1 Introduction

The scientific community, almost unanimously, considers that climate change is already happening (McNutt 2013; Deschenes and Greenstone 2007; Thornton et al. 2014; Rosenzweig and Parry 1994). The Intergovernmental Panel on Climate Change (IPCC) has clearly stated that human activities are altering the climate system and will continue to do so in the immediate future (IPCC 2014). Climate change will have negative effects on multiple economic and social indicators. Nonetheless, due to heterogeneity in both exposure and vulnerability those effects will vary across countries, regions, communities and individuals (Yamamura 2015; Bui et al. 2014; Mendelsohn et al. 2006). Poor households will face more difficulties to respond to and recover from climate variability than non-poor households. In addition, regions with more poverty and inequality are often also the regions more exposed to climate variability (Winsemius et al. 2015; Fothergill and Peek 2004). In these regions rural households tend to rely on agriculture, and natural resources in general, for at least part of their income (Cavendish 2000; World Bank 2002; WRI 2005). Given that agriculture is highly sensitive to climate there is a growing concern that, as a result of climate change, poverty in the rural sector might increase (Winsemius et al. 2015; Skoufias et al. 2011).

In many countries there is a lot of heterogeneity across rural households, this implies that some households might be more capable to adapt to climate change than others. Inequality might rise if some households can adapt to climate change

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while others are not able to do so. Therefore, understanding the link between climate change, poverty and inequality is crucial for the formulation and implementation of adaptation and mitigation policies (Ahmed et al. 2009; Hertel and Rosch 2010). According to Eriksen and O'Brien (2007) we need to study the effects of climate change on poverty an inequality in order to attain sustainable development in the XXI century. Nevertheless, the analysis of the potential effects of climate change on income distribution and poverty have received limited attention (Yamamura 2015; Bui et al. 2014; Hertel and Rosch 2010; Mideksa 2010) compared to the widely analyzed effects that it could have on the global economy (e.g., Stern (2007) and Nordhaus (2008)). A notable exception to this is the work of Leichenko and Silva (2014), who perform a thorough analysis of the relationship between climate change, vulnerability and poverty. They emphasize the need to recognize that poverty increases the likelihood that a given individual or household will be affected by climate change or by the aftermath of extreme climatic events. On the other hand, it should be acknowledged that the effects of climate on poverty are the result of the interactions among a series of dynamic and multidimensional social, economical, political and environmental processes, as well as by individual and community characteristics (Leichenko and Silva 2014).

Mendelsohn et al. (2006) and Tol et al. (2004) present some of the first efforts to analyze the potential effects of climate change on income distribution across countries. Both studies provide evidence supporting the hypothesis that the poor may bear most of the burden of economic damages from climate change. Similarly, Dell et al. (2008) use data for each country in the world from 1950 to 2003 to find evidence of a negative effect of higher temperatures on the growth level of poor countries. Nevertheless, since different socioeconomic groups and different regions within a country will experience different effects, these studies provide an incomplete picture of the effects of climate change. (Mendelsohn et al. 2006; Dell et al. 2009). As a way to overcome this limitation, Mendelsohn et al. (2007) use the Ricardian method to find a link between climate change and per capita income in a disaggregated way. Using cross section information for the U.S. (county level) and for Brazil (municipality level) they find that global warming will decrease rural income. Seo and Mendelsohn (2007) use a similar methodology to find that in South America farmers could lose up to 62% of their revenue due to severe scenarios of climate change. For Mexico, Mendelsohn et al. (2010) find average losses of land value between 42 and 54%. None of these studies measure poverty or inequality directly but all of them argue that poverty will increase or that the poor will be relatively more affected by climate change.

Mideksa (2010), uses a computable general equilibrium model (CGE) as an alternative to the Ricardian method and shows that in Ethiopia inequality could increase in as much as 20% as a response to climate change. Ahmed et al. (2009) and Hertel et al. (2010) use a CGE, which includes a poverty module, to look at poverty impacts of climate change in a group of developing countries. More specifically, Ahmed et al. (2009) examine productivity shocks due to extreme adverse climate events; the largest poverty impacts that they find occur in Africa. Meanwhile, Hertel et al. (2010) look at gradual climate change impacts through three scenarios of crop productivity changes. Their results show poverty rates increasing by 20–50% for non-agricultural households in parts of Africa and Asia. Jacoby et al. (2011) use a modified Ricardian model allowing for joint changes in the prices of land, labor and food, as a consequence of climate change. They find that, by 2040, the national poverty rate in India could increase in 3.5 percentage points as a consequence of climate change.

More recently there has been a surge of research that looks at the effects of natural disasters on the wellbeing of the households affected by them. Among them Bui et al. (2014) find that natural disasters have strong negative effects on poverty and income inequality in Vietnam. Meanwhile, Winsemius et al. (2015) use panel data for 52 countries to show that the poor, in particular those living in urban areas, tend to be more exposed to the negative effects of climatic events like droughts and floods. Yamamura (2015) use panel data for 86 countries for the period 1965–2004 to analyze how the incidence of natural disasters has affected income inequality. He shows that although natural disasters increase income inequality in the short run (5 years), the effect disappears after 10 years. Rodriguez-Oreggia et al. (2013) use panel data to show the effects that natural disasters have on the index of human development as well as on poverty at the municipal level in Mexico; this is the only analysis of its kind for the country. Their results show that droughts and floods lead to significant reductions in human development as well as to increases in poverty. It is important to note that Rodriguez-Oreggia et al. (2013) use municipal level data instead of household level data as we do in the present chapter.

This chapter presents results of the relationship between climate change and poverty and inequality at the household level. The specific channel of transmission that we analyze is agricultural income. Our focus is Mexico, both at the national and regional levels. It is relevant to analyze Mexico since even though there is evidence that it is vulnerable to climate change (Ahmed et al. 2009; Mendelsohn et al. 2010; Skoufias and Vinha 2013) very few studies have examined the potential poverty and inequality impacts in a disaggregated way.[1] Furthermore, the data set used allows us to estimate the potential poverty and inequality impacts of climate change at the regional level.

3.2 Methods

The relationship between agricultural productivity and climate variables as well as between climate variables and land values or net agricultural revenues has been clearly established (Mendelsohn et al. 1994, 1996, 2001). There is also evidence showing that rural households' income is affected by climate, with agricultural income being the mechanism of transmission (Mendelsohn et al. 2007). Although agricultural income is by no means the only transmission mechanism between cli-

[1]The present study extends the work presented in Lopez-Feldman (2013) by including and analysis of the effects on inequality; more importantly, in the present work we use more precise and updated climate projections.

mate and income it is the more direct and the one that has been more carefully analyzed (Mendelsohn 2009).[2]

In this chapter we look at the impacts of climate change (increases in temperature and changes in precipitation patterns) on agricultural income (crop and livestock). To do so, we follow a partial equilibrium approach in which there are no price changes. This approach allows us to look at potential effects at the household level knowing exactly where the effects are coming from. Its main disadvantage is that other effects that may arise from the impact of climate on agriculture (e.g., indirect effects through factor markets and effects through non-priced goods) are overlooked.

In order to estimate the relationship between agricultural income, temperature and precipitation we follow the Ricardian method (Mendelsohn et al. 1994). This method assumes that farmers will seek to maximize net farm revenues; its main advantage is its ability to implicitly incorporate private adaptation to climate conditions. It is worth mentioning that there is a recent series of papers (Di Falco et al. 2011, 2012; Di Falco and Veronesi 2012) that use a modified version of the Ricardian method in order to explicitly model endogenous adaptation decisions at the household level. Unfortunately, the data that we have does not allow us to model adaptation in an explicit way.

Following Mendelsohn et al. (1994, 2007, 2010) we use a reduced-form econometric specification that assumes a non-linear relationship between climatic variables and agricultural income. The general form of the equation estimated is the following:

$$yagr_i = \alpha + \beta_1 tem_i + \beta_2 tem_i^2 + \beta_3 pre_i + \beta_4 pre_i^2 + \boldsymbol{\delta} z_i + u_i \tag{3.1}$$

where $yagr_i$ is per capita household's net agricultural income, tem_i and pre_i are temperature and precipitation, z_i is a vector of household and geographic characteristics and u_i is an error term. This simple specification has been shown to be very effective to econometrically model the relationship between agricultural income and climate change in developing countries (Mendelsohn et al. 2010). Notwithstanding this, as pointed out by Deschenes and Greenstone (2007) there might be some problems with the use of cross sectional data to obtain consistent estimations of the effects of climate on land values (or on net income as we do here). The econometric estimation includes a series of control variables as a way to partially overcome this problem.

Once Eq. (3.1) is estimated, we use the coefficients as well as projected temperature (tem_i^{cc}) and precipitation (pre_i^{cc}) data from three climate change models (see next section) to calculate three versions of predicted agricultural income in a future with climate change ($yagr_i^{cc}$). That is, future agricultural income is estimated according to the following formula:

$$yagr_i^{cc} = \hat{\alpha} + \widehat{\beta_1} tem_i^{cc} + \widehat{\beta_2}\left(tem_i^{cc}\right)^2 + \widehat{\beta_3} pre_i^{cc} + \widehat{\beta_4}\left(pre_i^{cc}\right)^2 + \hat{\delta} z_i + u_i \tag{3.2}$$

where the control variables in z_i are taken at their current levels.

[2]Dell et al. (2009) and Horowitz (2009) propose to look directly at the relationship between total income and climate as a way to completely circumvent the need to rely on specific assumptions about the transmission mechanisms and how they might operate, interact and aggregate.

In order to calculate future total income we follow an approach of arithmetic microsimulations under the assumption that households' behavior does not change overtime (Bourguignon and Spadaro 2006).[3] Total simulated net income (y_i^{cc}) for each household is defined as the sum of simulated agricultural income and observed non-agricultural income (i.e., $y_i^{cc} = yagr_i^{cc} + ynagr_i$). For households that do not participate in agricultural activities (non-agricultural households) total simulated net income is equal to observed non-agricultural income (i.e., $y_i^{cc} = ynagr_i$).

Under the assumption that climate variables are the only thing that changes in the future, the final step to simulate the potential impacts of climate change is to compare the estimations of current poverty and inequality with their simulated versions. To estimate poverty we use the three main variants of the FGT poverty index proposed by Foster et al. (1984). The FGT index is calculated using the following formula:

$$FGT(\alpha) = \frac{1}{N}\sum_{i=1}^{N} I_i\left(1 - \frac{y_i}{q}\right)^{\alpha} \tag{3.3}$$

where $I_i = 1$ if $y_i \leq q$ and zero otherwise. Per capita income is represented by y_i, q is the poverty line, N is the population size, and α is a weighting parameter that can be interpreted as a measure of poverty aversion. When $\alpha = 0$ the formula collapses to the incidence or headcount index of poverty, in this case it represents the proportion of households considered as poor with respect to the total number of households. The headcount is an intuitive measure and it is easy to interpret, nonetheless, it has important shortcomings. The most important one is the fact that the headcount does not increase if a negative shock only affects households that were already below the poverty line before the shock.

We can classify the households that could be affected by climate change in two categories according to their income level before the shock: households with income above and households with income below the poverty line. The poverty headcount helps us understand the effects that climate change could have on the first group but not on the second. In order to be able to estimate the effects of climate change on the second group we need to use two other measures: the poverty gap and the poverty severity. When $\alpha = 1$ we obtain the poverty gap, which captures how far from the poverty line is the average income of the households that are below it. Imagine a negative shock that affects only households that were already below the poverty line, if the income of those poor households goes down then, contrary to the poverty headcount, the poverty gap goes up. The third measure, the poverty severity, is the result of setting $\alpha = 2$. This measure, in addition to being sensitive to changes in the income of households below the poverty line, gives more weight to the households that are further away from the poverty line.

[3]The underlying assumption is that households' participation in agricultural activities is not altered in response to climate change. That is to say, households that currently participate in agricultural activities will continue to do so while those not participating will continue that way.

In order to measure income inequality we calculate the Gini Coefficient, the most commonly used inequality measure both in academia and in public policy, according to the following formula:

$$G = \frac{-(N+1)}{N} + \frac{2}{N^2 \mu_y} \sum_{i=1}^{N} i \cdot y_i \tag{3.4}$$

where per capita income (y_i) is ordered from lowest to highest, and μ_y is average income (Fields 2001). The Gini Coefficient can take values between 0 and 1; a value of 0 means perfect equality and a value of 1 means perfect inequality.

After we calculate simulated income for each one of the three climate models, we proceed to estimate the FGT measures and the Gini Coefficient. By comparing these results with the FGT measures and Gini that we obtain using observed income we can uncover the potential effects of climate change on poverty and inequality.

3.3 Data

The data used in this research, with the exception of the climate data, comes from the Mexico National Rural Household Survey (ENHRUM by its acronym in Spanish). This survey provides detailed data on socio-demographic characteristics, production, and income sources from a nationally and regionally representative sample of rural households surveyed in 2003 (the information collected is for 2002). The sample is representative of more than 80% of the population that the Mexican census office (INEGI) considers to be rural and includes more than 1700 households from 80 villages in 14 states. In the analysis we use the 1552 households for which the necessary information is complete.[4] During the implementation of the survey Mexico was divided into five regions: South-Southeast, Center, West-Center, Northeast, and Northwest.

Climate change studies typically use climatologies for the period 1961–1990 as the baseline to then calculate climatic anomalies with respect to that period for temperature and precipitation (New et al. 2000). With such information variations of precipitation and temperature under different emissions scenarios can be calculated. We follow the same approach and use the climatologies for monthly surface temperature and monthly accumulated precipitation elaborated by the "Grupo de Cambio Climático y Radiación Solar del Centro de Ciencias de la Atmósfera of the Universidad Nacional Autónoma de México".[5] The elaboration of those climatologies explicitly considers the geographic location of ENHRUM communities. Conde et al.

[4]There are no statistically significant differences between households excluded from the analysis and those included. The only difference is that households excluded had missing information for one or more of the variables used in the econometric analysis.

[5]Recent work, for example Lobell et al. (2011), uses daily temperature and precipitation to measure climate impacts on crop yields. Unfortunately, daily measures and predictions on how they will

(2011), taking into account the representativeness criteria suggested by the TGICA-IPCC, identify the climate models that better represent the climatic uncertainty for the Mexican case. That is to say, the models that more efficiently incorporate the appropriate range of temperature increases but also, and more importantly, of increases as well as decreases in precipitation. Following the recommendations of that study in the present chapter we use the following models: MIROC 3.2, HADGEM1 and ECHAM5. We use information at the locality level for the period 1961–1990 to generate quarterly average temperature and accumulated precipitation. Climatology simulations for each locality are generated for both temperature and precipitation using the three models and the emissions scenario A1B; the simulations are for the period 2046–2055.

3.4 Results

3.4.1 Econometric Estimation

In order to estimate the relationship between agricultural per capita income and climate variables we follow Deressa and Hassan (2009) and Mendelsohn et al. (2010) and estimate Eq. (3.1) using quarterly values of temperature and precipitation. The vector z_i includes the gender and age of the household head; a wealth index created using variables that measure dwelling characteristics (number of rooms, availability of a separate room exclusively intended for cooking, presence of a bathroom, quality of construction materials, and availability of electricity and sewage) as well as dummy variables capturing ownership of durable goods (television set, refrigerator, car and agricultural equipment)[6]; the distance from the community to nearest city; altitude and latitude of the community; a subjective measure of land quality; availability of irrigation[7]; and regional dummies.

Table 3.1 shows the results of the econometric estimation, performed using ordinary least squares with weighted data to take into account the survey design. The dependent variable is net agricultural (crop and livestock) income for the 1000 households that participated in the activity in 2002. We estimated four specifications of the model. In the first one we only include climatic variables, then we add gender and age of the household head as well as the wealth index, in the third one we add community level characteristics, the last model includes irrigation and quality of the

change in response to climate change are not readily available. In particular, they are not available for the communities studied in this research.

[6]This index was created using principal components analysis and it captures the largest amount of information common to all the dwelling and durable goods variables. The methodology is explained in Filmer and Pritchett (2001). The Stata command pca was used to estimate the index.

[7]The assumption here, as in most of the literature is that irrigation is exogenous. An alternative will be to estimate a structural Ricardian model with irrigation as an endogenous variable as in Kurukulasuriya et al. (2011), but that is beyond the scope of this work.

Table 3.1 Per capita income (observed and simulated) and agricultural participation rates

	National	South-SE	Center	West-Center	NW	NE
Observed income						
	12,145	8,520	12,720	14,258	23,235	16,975
Simulated income						
MIROC	11,249	8,691	11,844	12,233	20,368	15,350
HADGEM	10,064	6,799	10,259	11,746	21,345	15,412
ECHAM	10,406	6,963	10,410	12,111	21,812	17,663
Households in agricultural activities						
	64%	85%	83%	69%	33%	47%

land in addition to all the other variables. The results are very stable across specifications; therefore, we focus on discussing the last specification, which is the one that we use later on in the simulation. Results for the control variables show that households headed by a male, as well as those with more wealth have significantly higher agricultural incomes. Agricultural households have considerably higher incomes if they are located in the Northeast part of the country. Land quality, measured by the fraction of cultivated land that is reported by the household as being of good quality, has a positive and significant effect on agricultural income. Finally, results show that the coefficients for fall and winter temperatures as well as summer, fall and winter precipitation have a statistically significant effect on agricultural income.

3.4.2 Simulations

What does this mean in terms of the potential implications of climate change on poverty? Before answering that question it is important to remember that the climate simulations, as well as the climate normals, vary for each one of the communities, therefore, deviations of temperature and precipitation from its climate normals will have heterogeneous effects across localities. To try to capture those effects we follow the methodology described in Sect. 3.2 to simulate, for each one of the 1552 households, total per capita income using the climate change predictions from the three climate models. The first column of Table 3.2 compares observed income with the three version of simulated income at the national level.[8] Results show a significant impact of climate change; the reduction in average total per capita income is between 7 and 17%.

Although these national level results are informative they mask the heterogeneity across regions and therefore the potential heterogeneity in welfare impacts. The

[8]Income is shown in Mexican Pesos. The exchange rate during the period was roughly 10 pesos/dollar.

Table 3.2 Econometric estimation of Ricardian model for Rural Mexico

	(1)		(2)		(3)		(4)	
	Coefficient	t	Coefficient	t	Coefficient	t	Coefficient	t
Spring temp	−11,518.3	−1.21	−11,757.7	−1.24	−20,568.1*	−1.82	−18,476.7	−1.62
Spring temp^2	203	1.1	208.9	1.15	394.9*	1.79	363.5	1.64
Summer temp	−6,412.4	−0.42	−4,686.1	−0.31	20,498.6	1.11	18,419.9	1
Summer temp^2	86.41	0.3	43.42	0.15	−405.5	−1.21	−373.3	−1.11
Fall temp	39,815.1***	3.97	42,994.2***	4.33	35,242.9***	3.57	34,736.5***	3.51
Fall temp^2	−808.2***	−3.33	−888.7***	−3.7	−710.9***	−3.06	−693.2***	−2.98
Winter temp	−43,472.6***	−4.37	−46,305.4***	−4.73	−42,581.3***	−4.4	−42,229.2***	−4.36
Winter temp^2	965.0***	3.72	1045.3***	4.1	890.0***	3.41	877.2***	3.35
Spring prec	197.1***	3.34	204.0***	3.46	97.58	1.2	97.5	1.2
Spring prec^2	−0.360***	−2.94	−0.372***	−3.08	−0.218	−1.64	−0.216	−1.63
Summer prec	−109.9**	−2.41	−110.7**	−2.43	−129.3***	−2.66	−128.2***	−2.65
Summer prec^2	0.119**	2.47	0.111**	2.35	0.148**	2.46	0.145**	2.42
Fall prec	241.5***	3.21	241.2***	3.2	217.8***	2.79	212.6***	2.69
Fall prec^2	−0.293***	−3.43	−0.284***	−3.35	−0.264***	−3.01	−0.254***	−2.86
Winter prec	141.4	1.08	141.3	1.08	122.4	0.95	115.3	0.89
Winter prec^2	−1.291***	−3.46	−1.335***	−3.59	−0.642*	−1.67	−0.642*	−1.69

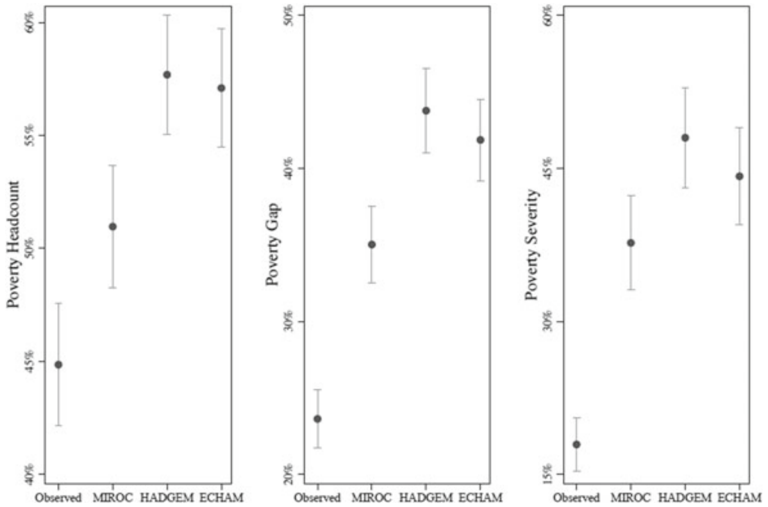
(continued)

Table 3.2 (continued)

	(1)		(2)		(3)		(4)	
	Coefficient	t	Coefficient	t	Coefficient	t	Coefficient	t
Gender			1822.9***	4.17	1,763.3***	4.09	1,554.1***	3.67
Age			27.84	1.39	24.93	1.28	21.67	1.14
Wealth index			4317.0***	4.28	4,700.0***	4.31	4,625.3***	4.25
Distance					−0.00833	−0.97	−0.00858	−1
South-Southeast					2,384.7	0.78	1,342.8	0.44
Center					3,987.2	1.27	2,904.3	0.92
West-Center					3,902.0	1.44	3,510.7	1.31
Northeast					10,500.8***	2.91	10,280.9***	2.86
Latitude					−3,067.1	−1.34	−2,946	−1.28
Altitude					1.679*	1.83	1.701*	1.84
Good land							1,283.2*	1.9
Irrigated land							41.77	1.63
Constant	228,672.7**	1.98	203,618.0*	1.76	101,344.8	0.74	101,162.1	0.74
Observations	1000		1000		1000		1000	
R^2	0.09		0.111		0.124		0.132	

Note: *, **, *** significant at 10%, 5%, and 1%, respectively regions where more households are involved in agricultural activities are the South-Southeast and the Center (85 and 83%, respectively) followed by the West-Center (69%). In the Northwest only 33% of the rural households participate in agricultural activities while 47% do it in the Northeast. The regional distribution of negative impacts of climate change on total income follows a similar pattern with the South-Southeast and the Center experiencing the biggest potential impacts (−20 and −19%, respectively) while the Northeast will suffer the smallest impact (−10%). Overall these results show a clear negative effect of climate change on simulated income.[9]

Using the information on observed per capita income we know that 45% of rural households in Mexico were below the poverty line in 2002.[10] Figure 3.1 shows that, according to the three climate models and their corresponding income simulations, climate change can have considerable impacts on poverty. Simulated poverty headcount is above 50% for the MIROC model and above 55% for the HADGEM and ECHAM models. The highest value (58%), corresponding to the HADGEM model, implies that in a scenario with climate change an additional 350,000 rural households will be below the poverty line compared to the baseline scenario.[11] The relative increases in the poverty gap and in poverty severity are even bigger, reflecting



90% confidence intervals

Fig. 3.1 Effects of different climate scenarios on poverty (National level)

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[9]It is important to notice that in a couple of instances simulated income is predicted to be above current income.

[10]For the measurement of poverty we use the official food poverty line for rural Mexico for the year 2002, 5937.36 pesos per year (CONEVAL 2006).

[11]The expansion factors used in the survey design and incorporated in the estimations presented here imply that the households in the sample represent 2,726,805 rural households.

the fact that, according to the simulations, those already below the poverty line will be significantly affected by climate change.

On the other hand, poverty is not homogeneously distributed across the country; more than 60% of rural households in the South-Southeast are below the poverty line while only 19% have the same status in the Northwest. Figure 3.2a shows heterogeneous effects of climate change on poverty at the regional level. For the South-Southeast the simulated poverty rates for the HADGEM and ECHAM models are 74% and they are statistically different from the observed level of poverty. The estimates for the MIROC model show are reduction in poverty but the result is not statistically different from the poverty estimated with observed income. The region with the highest relative change in simulated poverty is the West-Center, where poverty can increase in as much as 17 percentage points, equivalent to 125,000 additional households below the poverty line. For the rest of the regions the changes in poverty are high as well; even in the north the MIROC and HADGEM models predict statistically significant increases in the number of households that are below the poverty line. Figure 3.2b, c shows that agricultural households that are already poor could be considerably affected by climate change. The highest increase in the absolute value of the poverty gap happens in the Center, while the highest relative increase is predicted for the Northwest. For poverty severity the highest absolute predicted impacts are registered in the north with the highest relative increase in the Northwest. This implies that, even though in the Northwest and Northeast not many rural households participate in agriculture, those that do it are highly vulnerable to changes in precipitation and temperature caused by climate change.

Inequality in rural Mexico was relatively high in 2002, reaching 0.58 in the Gini Coefficient according to observed total income. As Fig. 3.3 shows inequality would increase considerably due to climate change, reaching a point estimate of 0.71 using the income simulated after the HADGEM scenario. Figure 3.4 shows that similar trends can be expected in all the regions. The region with the least inequality, according to observed income, is the West-Center with a Gini of 0.48, while the Northeast is the region with more inequality (0.63). According to the simulations, the South-Southeast region could experience the highest increase in inequality due to climate change, passing from 0.62 to 0.82, although only the HADGEM model leads to an increase that is statistically significant.

3.5 Conclusions and Final Remarks

In the economics literature it has been frequently mentioned that climate change can have an important effect on welfare, however, quantitative estimates of impacts at the household level are very scarce. This chapter uses data from ENHRUM 2002 to estimate the potential effects of climate change on poverty and inequality. Results show that fluctuations in climatic variables (temperature and precipitation) increase poverty and inequality for Mexican rural households. Our results show that, given the current levels of participation in the agricultural sector, a change in climate could lead

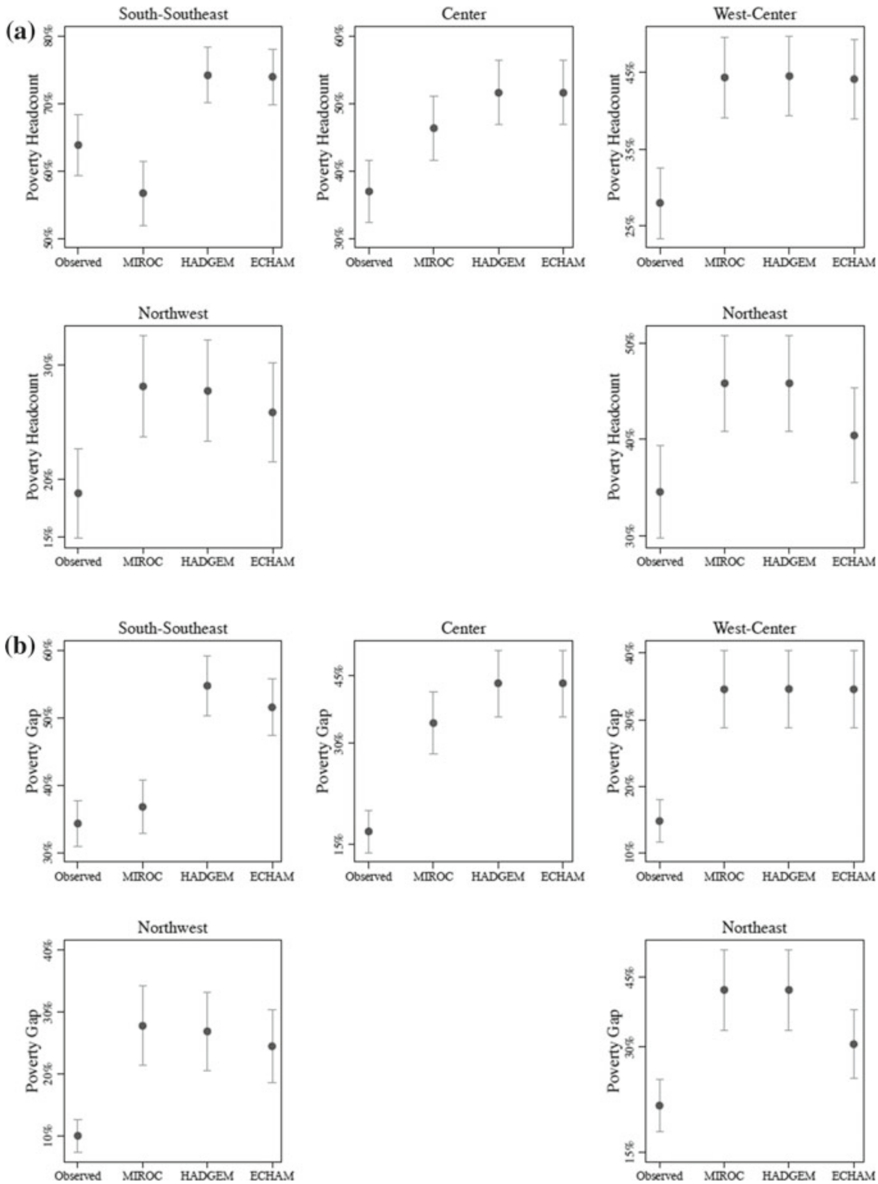

Fig. 3.2 Effects of different climate scenarios on poverty (Regional level)

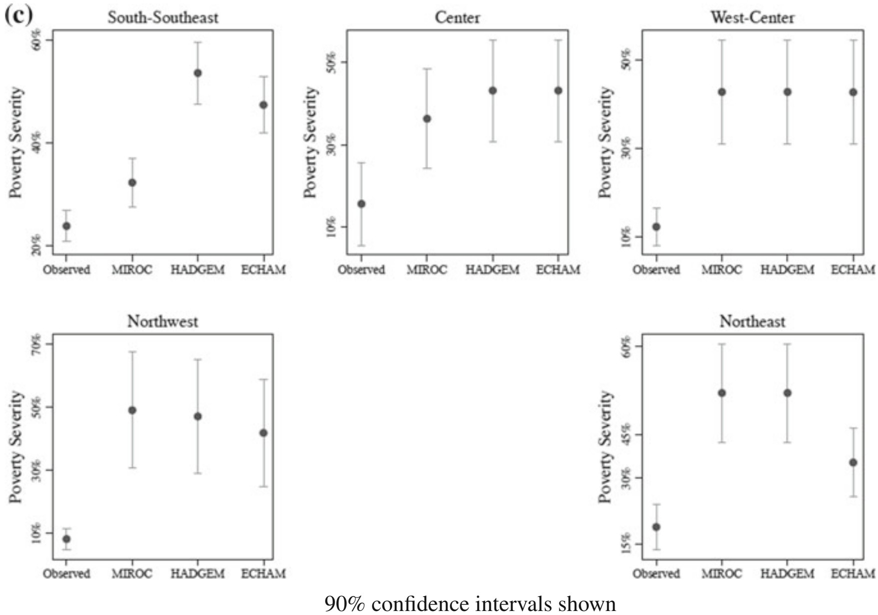

Fig. 3.2 (continued)

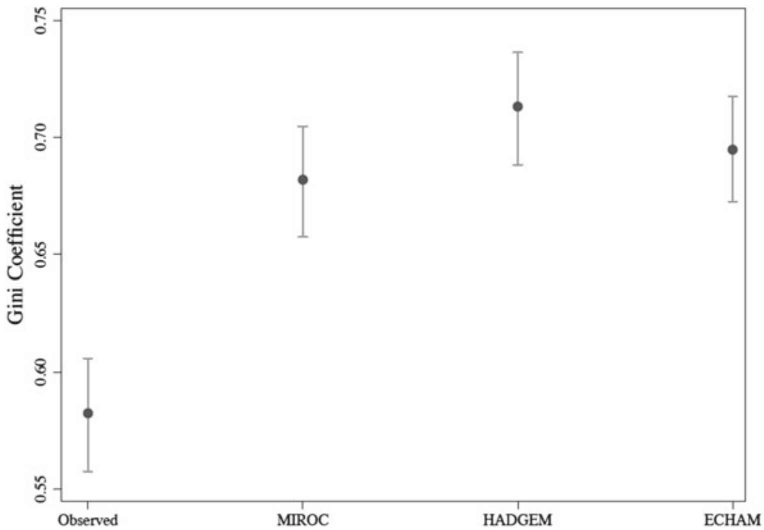

Fig. 3.3 Effects of different climate scenarios on inequality (National level)

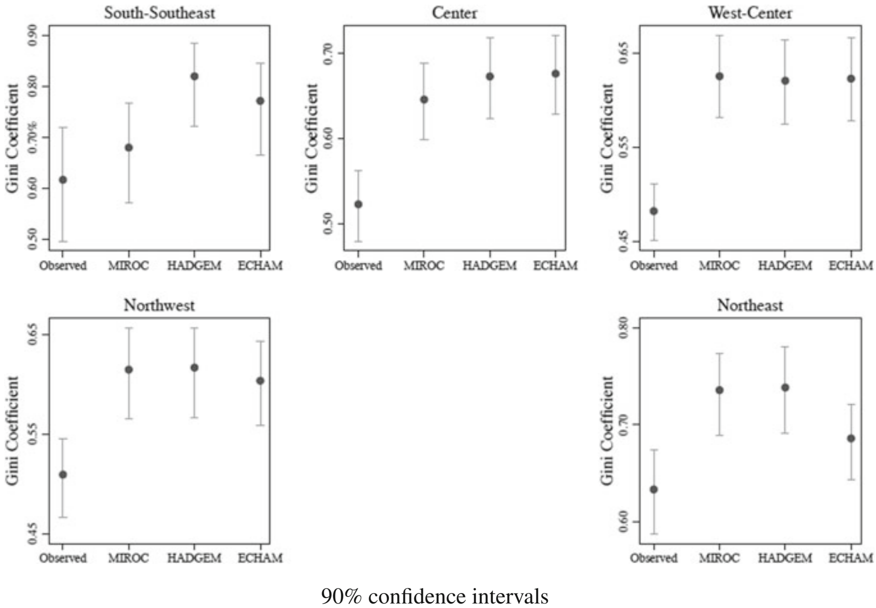

Fig. 3.4 Effects of different climate scenarios on inequality (Regional level)

to an additional 350,000 households below the poverty line in rural Mexico. Of those households, slightly more than 35% will be located in the West-Center and almost 35% in the South-Southeast. It is important to emphasize that these results are not forecasts, they are simply indicative of the magnitude and geographical distribution of the potential climate change impacts given the current conditions. This is due to the fact that the methodology used has some important limitations (e.g., extreme climatic events are not included and prices are taken as given and constant, indirect impacts through factor markets are not included, and participation in the agricultural sector is kept constant) and to the intrinsic uncertainty about how will the world look like by the end of the century. A particularly strong assumption in this sense is that farms in the future remain essentially as they are today. Of course, technology adoption and increased capitalization is likely to happen in rural Mexico and this will have an impact on the sensitivity of income to climate. Notwithstanding these limitations, this chapter is a contribution to the very limited literature on quantitative estimates of climate change impacts at the household level.

Although climate change is certainly not the cause of poverty and inequality it can certainly exacerbate it. The present work has shown that in countries with high exposure and vulnerability to climate change, like Mexico, agriculture is a channel by which climate change can have negative effects on the wellbeing of rural households. We consider that future research should take into consideration non-monetary dimensions of poverty but more importantly it should delve into the understanding of the conditions that facilitate the adaptation of the poor to climate change.

Promoting the adaptation capacity of the population, especially of the poor, should be a priority of those developing countries that are highly exposed to the impacts of climate change, like Mexico. Although from the results one might be tempted to infer that the impacts of climate change can be ameliorated by policies aimed to reduce households' dependence on the agricultural sector (e.g., promotion of off-farm employment), a more thorough methodology (e.g., combining econometric estimations with a disaggregated rural economywide model) is necessary to adequately simulate the implications that different policies might have under different climate change scenarios.

So far most of the adaptation efforts have focused on reducing risk. We consider that the focus should change towards improving local adaptation capacity as well as to modifying the social processes that increase vulnerability. Reducing poverty and inequality can be seen as a necessary condition to achieve this. As our results show, the effects of climate change are heterogeneous across regions; this reflects fundamental differences in the local contexts that should be taken into account when designing adaptation policies that are locally relevant. This does not imply that the promotion of adaptation and the reduction of vulnerability should be seen exclusively as a local endeavor, on the contrary, many of the preconditions necessary to achieve such goals require changes in the political and economic institutions at the national level.

Further research is necessary to better understand the way in which farmers might adapt over time to a changing climate that has persistent and potentially generalized effects. In particular, the results presented here are based on a model that allows for adaptation to climate change in a partial equilibrium model with no price changes. Nevertheless, climate change is likely to lead to changes in prices of agricultural products and inputs and might have impacts that cannot be anticipated with the framework used here.

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Chapter 4
The Value of Meteorological Information in Agrarian Producers' Decision Making: Introducing Analytic Decision Models

Emilio Cerdá, Sonia Quiroga and Pablo Martinez-Juarez

4.1 Introduction

The value of weather information is relevant to society (Leviäkangas and Hautala 2009; Frei 2010; Wu et al. 2014), both because of its influence on agriculture (Regnier 2008) and on water resources (Freebairn and Zillman 2002). Meteorological information affects agrarian production due to its capacity of modifying their decisions. Farmers use meteorological forecasting to manage their activities, using information on meteorological variables in order to decide when to sow, when to harvest and to decide their use of pesticides (McNew and Mapp 1990). The value of the information will, in general, depend on the specific context of the problem being addressed. Therefore, the literature necessarily consists of individual case studies rather than of general results (Adams et al. 2003; Anaman and Lellyett 1996b). Katz and Murphy (1997) review the existing literature on studies trying to economically value meteorological information.

Setting aside studies related to the impact of meteorological impacts over the economy [studies such as that performed by Roll (1984)] which mainly focus over isolated impacts of meteorological events over market prices, and directing our attention in the issue of the value of information, it is possible to differentiate between empirical evaluation studies and theoretical approaches linked to decision theory.

Among empirical valuation studies, it is possible to find normative as well as descriptive analyses. The value of meteorological information, for both types of studies, is derived from the effects that this information has on individual decisions

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linked to any climate-related activity. Methods used in order to develop decision-making models and the criteria for their evaluation is what differentiates between approaches.

Descriptive, or positive, studies not always finalise their approach by modelling the information obtained, but often focus on aspects that represent a non-optimal behaviour instead. Their main use is to enrich other models.

Descriptive studies are evaluated according to their capacity to faithfully reproduce agents' behaviour.

On the other hand, normative studies provide, under certain assumptions, specific figures for the value of weather forecasts. Those are valuations of very particular cases, almost all of them developed in an agricultural environment. It is not possible to extrapolate them to find the value of such information in a whole sector or an entire economy. However, they provide an important motivation by giving a measurement of the problem to some extent.

In that sense, normative studies are evaluated according to their ability to find decisions that are optimal according to one normative decision theory or another. They do not need to be evaluated according to the actual behaviour of agents. The differences between actual agent behaviour and the model are expected, as agents do not necessarily follow the normative models in their decision-making processes.

Davis and Nnaji (1982) compiled a list of the information necessary in order to empirically estimate the value of information: (i) a function of payments and an information-based decision rule; (ii) a probability distribution conditioned to the status of nature given that information; (iii) a probability distribution over the information that could be generated; (iv) the mean number of informative events for time unit; (v) all users of the information, their decision rules and their payment functions; (vi) the cost of the information.

Within agricultural decision problems, a few areas have received the most attention. Wilks (1997) makes a review of the literature referring to this issue and concludes that the majority of the studies are clustered in the following groups: the production of raisins, the protection against frosts, irrigation, the preservation of the forage, crop selection and fertilization management. A summary of these studies can be seen in Table 4.1.

One of the main reasons for using this analytical decision framework from the more theoretical point of view is, the need to compute the potential value of information at the individual level in a more generic framework, due to the context-specific nature of this information.

A good theoretical approach to meteorology-sensitive decisions, those taken under uncertainty, is the construction of the so-called analytical decision models (see Clemen 1996; Keeney 1982; Winkler and Murphy 1985; Winkler et al. 1983). These are models that, simple in their structure, capture some of the essential facts of real situations, in particular their dynamics.

Table 4.1 Individual assessment studies of the meteorological information reviewed in Wilks (1997)

Researchers	Objective	Valuation method
Baquet et al. (1976)	Valuation of frosts for pear crops	Bayesian, Expected utility maximisation
Katz et al. (1982)	Valuation of frosts' forecasts for Yakima Valley farmers	Bayesian, Expected spending minimisation
Stewart et al. (1984)	Valuation of frost forecasts for apple crops in Yakima Valley	Bayesian, Expected spending minimisation
Wilks and Murphy (1985)	Valuation of precipitation forecast for the deciding between hay and pasture in Western Oregon	Bayesian, Expected utility maximisation
Hashemi and Decker (1972)	Irrigation programming in corn production	Bayesian
Ewalt et al. (1973)	Valuation of precipitation and soil condition forecast for farmers in Indiana	Survey (Subjective)
Lave (1963)	Valuation of improved meteorological information for the raisin industry in California	Cost-loss and impact over industry benefits
Tice and Clouser (1982)	Valuation of meteorological information for individual corn and soy producers	Accounting, maximisation of expected benefit
Byerlee and Anderson (1969)	Valuation of annual predictors of precipitation trends with response functions for wheat production	Bayesian, Expected benefit maximisation
Brown et al. (1986)	Valuation of seasonal climate forecasts for wheat producers in large plantations	Expected benefit maximisation
Sonka et al. (1987)	Valuation of seasonal climate for corn producers in Illinois	Expected benefit maximisation
Bosch and Eidman (1987)	Valuation of meteorological and soil water information for irrigation farmers	Expected Benefit, generalized stochastic dominance
Mjelde et al. (1988)	Valuation of seasonal climate for wheat producers	Bayesian, Expected value maximisation

(continued)

Table 4.1 (continued)

Researchers	Objective	Valuation method
Sonka et al. (1988)	Valuation meteorological forecasts over better production in the Midwest	Cost-loss
McGuckin et al. (1992)	Valuation of climate information over soil humidity for irrigation farmers	Average cost reduction
Anaman and Lellyett (1996a)	Valuation of an improved meteorological information for the Australian cotton industry based in producer surplus	Bayesian, maximisation of expected value
Solow et al. (1998)	Valuation of forecasts for the US, based in the expected economic surplus (sum of producer and consumer surplus)	Bayesian, expected value maximisation
Chen and McCarl (2000)	Valuation of information on the El Niño Southern Oscillation (ENSO) in terms of increased economic Benefit	Bayesian, expected value maximisation
Mjelde and Penson (2000)	Valuation of the impact of the use of climatic predictions over the agriculture sector, over consumers and producers	Bayesian, expected value maximisation
Hamlet et al. (2002)	Valuation of long term prediction of river water volume	Bayesian, expected value maximisation
Bert et al. (2006)	Estimation of the economic value of climatic information for corn production systems in the Argentinean Pampas	Adjustment of expected benefits
Leviäkangas et al. (2009)	Value of meteorological information in Finland based on crop protection, reductions in damages and harvest cycles	Literature availability
Wu et al. (2014)	Meteorological service effect on agriculture, forestry, husbandry, and fishery	Input-output method

The most important aspects that define any analytical decision model (Wilks 1997) are:

- Actions available for the agent.
- Possible states of nature.
- Probabilities associated with those states of nature.
- Known consequences of each action-state pair of nature.

The uncertainty is given by some meteorological variable that produces uncertain events. Weather forecasts help decision making by predicting the probability associated with such events. The economic value of these forecasts is taken as the difference between the expected benefit when an imperfect weather forecast is available, and the expected benefit when it has only basic information.

4.2 Calculating the Value of Information

Climatological information is the most commonly accepted basic information. That is, suppose that the agent knows the relative historical frequencies for meteorological events that affect its activity.

The optimal action is determined through formal mathematical models, this is, the emphasis is placed on obtaining analytical results: an optimal policy, or decision rule that specifies what action the decision maker should take based on the information received.

Formally, this type of problems can be expressed in a generic way:

Let A be the set of possible actions for the agent.

Let E be the set of possible states of nature.

$\forall a \in A,\ \forall e \in E$, the cost of carrying out the action a if the state of nature e is given, is expressed as $c(a, e)$ and it is perfectly known.

Given the probability distribution of E and being F its distribution function, which is known to the agent, the expected cost of choosing a certain action a would be:

$$E_E[c(a,e)] = \int_E c(a,e)dF(e)$$

Therefore, the decision problem, taking into account the minimising of expected costs criteria, consists on selecting a such that:

$$Min\ E_E[c(a,e)] = \int_E c(a,e)dF(e)$$

$$a \in A$$

A more specific case of this problem could be proposed with a finite set of actions (a_j) and of states of nature e_j.

$$A = \{a_1, \ldots, a_n\};\ E = \{e_1, \ldots, e_j\},$$
$$\forall i, j, i \in \{1, \ldots, n\},\ j \in \{1, \ldots, m\}$$

The cost of carrying an action a_i, given the e_j state of nature, can be expressed as $c(a_i, e_j)$ and is already known.

The agent knows also the probability of each state of nature occurring:

$P(e_j)$ is the probability of the state being e_j.

Therefore, $P(e_j) > 0$ and $\sum_{j=1}^{m} P(e_j) = 1$.

For each action a_i, the mathematical expected cost would be:

$$E_E[c(a_i, e_j)] = \sum_{j=1}^{m} c(a_i, e_j)P(e_j)$$

Which would imply that the problem of decision in this more concrete case, taking into account the minimization of cost criteria, could be expressed as:

$$Min\ E_E[c(a_i, e_j)] = \sum_{j=1}^{m} c(a_i, e_j)P(e_j)$$
$$a_i \in A$$

After this decision problem, it is possible to consider the effect of introducing additional information through a variable $z \in Z$, which could take the following values:

$$Z = \{z_1, \ldots, z_l\}\forall k,\ k\forall\{1, \ldots l\}$$

In that case, a revision of probabilities occurs, where conditional probabilities come into relevance. Those are also supposed to be known:

$P(e_j|z_k)$ is the probability of state being e_j once z has taken value z_k.

Therefore, $P(e_j|z_k) > 0,\ \sum_{j=1}^{m} P(e_j|z_k) = 1$.

In this case, the decision over which a_i action to carry out must be taken before knowing which the state of nature is. Nevertheless, the value of variable z is known at that specific point. That lies beneath its ability of giving additional information.

The decision in this case might depend on which the information received through variable z is.

Once z_k is known, for each action a_i, he expected cost would be:

$$\sum_{j=1}^{m} c(a_i, e_j)P(e_j|z_k)$$

And the decision problem, taking into account the minimisation of expected cost criteria, could be expressed as:

$$Min \sum_{j=1}^{m} c(a_i, e_j)P(e_j|z_k)$$
$$a_i \in A$$

Solving this problem, we obtain an optimal action a_i^* given z_k.

Therefore, a series of contingent optimal decisions a_i^* exist:

$$Z \to A$$
$$z_k \to a_i^*(z_k)$$

Once after that point, it is possible to calculate the concept of economic value of the information as the difference between the cost caused by the selected action known variable z, and the cost caused by the chosen action without any knowledge about variable z.

4.2.1 Cost-Loss Ratio Situation Model. Static Case

The model commonly referred as Cost-Loss Ratio Situation is a specification of prototype decision models used in a generical manner in the previous section.

Since 1950, meteorologists have payed special attention to the static version of this model (See, Thompson 1952, 1962; Thompson and Brier 1955; Murphy 1977). With a simple structure, the bibliography mentioned summarised the main traits of the problem faced by a farmer who has to decide over the protection given to a crop against meteorological adversities.

The simplified structure of the model is the following:

There exist two possible states of nature, in this case given by the values that can be taken by a variable θ, which expresses the meteorological situation:

- $\theta = 1$ if meteorological conditions are adverse for the crop.
- $\theta = 0$ if they are not adverse for the crop.

Facing these two possible states of nature, farmers can take two different actions: to protect their crops or not to protect them. The cost of protecting the crop is known and equal to C. Moreover, farmers know that they can face a loss L if they do not protect the crop and adverse meteorological conditions occur. The matrix of payments related to the problem is given in Table 4.2.

Meteorological information is of a categoric type, not a probabilistic one.

The individual associates a determined probability to adverse weather, this is what is understood as Climatological Information.

$$P_\theta = Pr\{\theta = 1\}$$

On the other hand, the agent could consider the incorporation of additional information to the model offered by meteorological information. We face imperfect information on θ in this case, which will be assumed Z.

Random variable Z can take the following values:

$Z = 1$ if prediction is for adverse weather.
$Z = 0$ if prediction is for non-adverse weather.

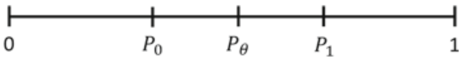
From the ex-post point of view, it can be defined as a categoric prediction.

This prediction system is simple, though it has the advantage of being totally characterised by two probabilities:

$P_1 = Pr\{\theta = 1|Z = 1\}$, the probability that, being the weather prediction adverse, adverse weather occurs.
$P_0 = Pr\{\theta = 1|Z = 0\}$, the probability that, being the weather prediction non-adverse, adverse weather occurs.

Without loss of generality, it can be supposed:

$$0 \leq P_0 \leq P_\theta \leq P_1 \leq 1$$



It can be noted that in the case of $P_0 = P_\theta = P_1$, we observe the case of climate information, while in the opposite extreme case, if $P_0 = 0$ and $P_1 = 1$, we witness the perfect information case.

- Sufficiency:

Let (P_0, P_1) and $\left(P_0', P_1'\right)$ be meteorological prediction systems. (P_0, P_1) can be considered sufficient of $\left(P_0', P_1'\right)$ if it is verified that:

$$P_0 \leq P_0' \leq P_\theta \leq P_1' \leq P_1$$

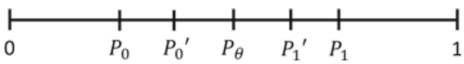


Table 4.2 Matrix of payments of the cost-loss ratio situation model

Action	States of nature	
	Adverse weather (θ = 1)	Non-adverse weather (θ = 0)
Protect	C	C
Not protect	L	0

This means, the system (P_0, P_1) offers added information with respect to the system $\left(P'_0, P'_1\right)$ for all agents.

- Assumption:

The adverse-weather prediction is given with the same probability (long-term relative frequency) than the occurrence of bad weather.

$$Pr\{Z = 1\} = P_\theta \tag{4.1}$$

Therefore,

$$P_0 = \frac{(1 - P_1)P_\theta}{(1 - P_\theta)}$$

En efecto:

$$\begin{aligned} P_\theta = \Pr\{\theta = 1\} &= \Pr\{\theta = 1|Z = 0\} \cdot \Pr\{Z = 0\} \\ &\quad + \Pr\{\theta = 1|Z = 1\} \ \cdot \Pr\{Z = 1\} = P_0(1 - P_\theta) + P_1(P_\theta) \Rightarrow \end{aligned}$$

$$\Rightarrow P_0(1 - P) = (1 - P_1)P_\theta P_0 = \frac{(1 - P_1)P_\theta}{(1 - P_\theta)}$$

This means, P_0 approaches cero at the same relative path as P_1 moves towards one.

A measure for quality q can be defined rescaling the probability for an adverse weather P_1:

$$q = \frac{P_1 - P_\theta}{1 - P_\theta} \quad 0 \le q \le 1$$

where:
$q = 0$ if only climate information is available
$q = 1$ if available information was perfect

It is verified that $q = Corr(Z, \theta)$, where $q = Corr(Z, \theta)$ denotes the coefficient of correlation of Z, θ.

En efecto:
Let us calculate: $Corr(Z, \theta) = Cov \frac{Cov(Z,\theta)}{\sqrt{Var(Z)}\sqrt{Var(\theta)}}$

Taking into account the expression (4.1):

$$z : \begin{matrix} 1 & 0 \\ P_\theta & 1 - P_\theta \end{matrix} \qquad \theta : \begin{matrix} 1 & 0 \\ P_\theta & 1 - P_\theta \end{matrix}$$

$$E(Z) = E(\theta) = P_\theta$$

$$Var(Z) = Var(\theta) = E\{\theta^2\} - \left[E\{\theta\}^2\right] = P_\theta - P_\theta^2 = P_\theta(1 - P_\theta)$$

$$Cov(Z, \theta) = E\{Z, \theta\} - E\{Z\}E\{\theta\}$$

Z, θ can take values 0 and 1 (as both Z and θ can only take values 0 and 1).

$$\begin{aligned} Pr\{Z\theta = 1\} &= Pr\{Z\theta = 1/Z = 1\} \cdot Pr\{Z = 1\} \\ &\quad + Pr\{Z\theta = 1/Z = 0\} \cdot Pr\{Z = 0\} \\ &= Pr\{Z\theta = 1/Z = 1\} \cdot Pr\{Z = 1\} + 0 = P_1 P_\theta \Rightarrow \end{aligned}$$

$$\Rightarrow Pr\{Z\theta = 0\} = 1 - P_1 P_\theta.$$

It can be obtained

$$E(Z\theta) = Pr\{Z\theta = 1\} = P_1 P_\theta$$

$Corr(Z, \theta) = \frac{E\{Z\theta\} - E\{Z\}E\{\theta\}}{\sqrt{Var(Z)}\sqrt{Var(\theta)}} = \frac{P_1 - P_\theta}{1 - P_\theta} = q.$

If $E(q)$ is the minimum expected spending for a quality level q of the meteorological predictions system, the Economic Value of Prediction can be defined as:

$V(q) = E(0) - E(q)$ for $0 \le 1 \le 1$.

Which, by definition gives us: $V(0) = 0$.

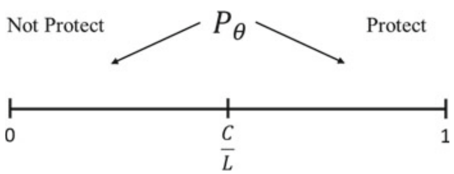
Structure of an optimum policy with only Climatological Information (P_θ):

Following Table 4.2:

- If the agent decides to protect, he will face a cost C.
- If the agent decides not to protect, the expected cost is $P_\theta L$.

Therefore, optimal policy takes the form:

(i) to protect if $P_\theta > \frac{C}{L}$
(ii) not to protect if $P_\theta < \frac{C}{L}$.



If $P_\theta = \frac{C}{L}$, there is a situation of indifference between protecting and not.

This implies that the minimum expected spending with climatological information would be:

$$E(0) = Min\{C, P_\theta L\}$$

<u>Structure of an optimum policy with imperfect Information (Z):</u>

Let us suppose the case where $0 < P_\theta < \frac{C}{L}$

If $Z = 0$, we have:

- If the agent protects the crop, the cost will still be C.
- If the agent decides not to protect, the expected cost will be $P_\theta L$.

Therefore, the individual will only protect the crop if $C < P_\theta L$. This is not a possibility, as $P_0 < P_\theta < \frac{C}{L}$. This implies that in this case, if $\mathrm{Z} = 0$, the agent will take the same decision as when only climatological information was available.

Nevertheless, if $Z = 1$:

- If the agent protects the crop, the cost will still be C.
- If the agent decides not to protect, the expected cost will be $P_1 L$.

Therefore, the agent will decide to protect if $C < P_1 L$.

By taking the definition of information quality index: $q = \frac{P_1 - P_\theta}{1 - P_\theta}$, the optimal decision when $Z = 1$, will be to protect if $\left[P_\theta + q(1 - P_\theta)\right]L > C$, Which can be verified when

$$q > \frac{\left(\frac{C}{L} - P_\theta\right)}{(1 - P_\theta)}.$$

Therefore, the optimal policy in the case when imperfect information is available could be specified as

$$\text{Let } q^* = \frac{\left(\frac{C}{L} - P_\theta\right)}{(1 - P_\theta)}.$$

If $0 \le q \le q^*$, it is never an optimal decision to protect. Consequently, $E(q) = E(0)$.

If $q^* \le q \le 1$, the optimum choice is to protect when $\mathrm{Z} = 1$, and not to procect when $Z = 1$. In this case:

$$E(q) = P_\theta C + (1 - P_\theta)P_0 L = P_\theta\left[C + (1 - P_\theta)(1 - q)L\right] \text{ if } q^* < q < 1\,.$$

Which implies that the value for the quality prediction of q would be:

$$V(q) = E(0) - E(q) \Rightarrow$$

$$\Rightarrow V(q) = \begin{cases} P_\theta\big\{\big[P_\theta + (1 - P_\theta)q\big]L - C\big\} & if\ q^* < q \le 1 \\ 0 & if\ 0 \le q \le q^* \end{cases}$$

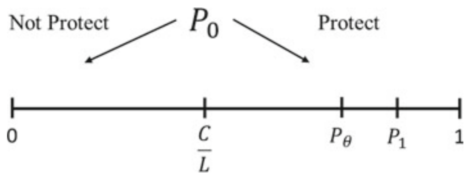
For the case where $\frac{C}{L} \le P_\theta < 1$ two analogue expressions can be obtained:

As $P_\theta \ge \frac{C}{L}$, it is $E(0) = C$.

As $P_0 \le P_\theta \le P_1$, it is $P_1 \ge \frac{C}{L}$, with two possibilities (i) $P_0 \ge \frac{C}{L}$, and (ii) $P_0 < \frac{C}{L}$.

If $Z = 1$, the optimal choice is to protect, as $P_1 \ge \frac{C}{L}$.

If $Z = 0, \Rightarrow \begin{cases} \text{To protect,} & if\ P_0 \ge \frac{C}{L} \\ \text{Not to prorect,} & if\ P_0 < \frac{C}{L} \end{cases}$



Therefore, the key issue lies in whether P_0 is higher or lower than $\frac{C}{L}$.

We know that:

$$P_0 = \frac{(1 - P_1)P_\theta}{1 - P_\theta} \tag{4.2}$$

Meanwhile, $q = \frac{P_1 - P_\theta}{1 - P_\theta} \Rightarrow$

$$\Rightarrow P_1 = P_\theta + (1 - P_\theta)q \Rightarrow 1 - P_1 = 1 - P_\theta - (1 - P_\theta)q = (1 - P_\theta)(1 - q)$$

Therefore,

$$P_0 = \frac{(1 - P_\theta)(1 - q)P_\theta}{1 - P_\theta} = (1 - q)P_\theta$$

So,

$$P_0 \ge \frac{C}{L} \Leftrightarrow (1 - q)P_\theta \ge \frac{C}{L} \Leftrightarrow P_\theta - qP_\theta \ge \frac{C}{L} \Leftrightarrow qP_\theta \le P_\theta - \frac{C}{L} \Leftrightarrow q \le 1 - \frac{\frac{C}{L}}{P_\theta}$$

Let $q^{**} = 1 - \frac{\frac{C}{L}}{P_\theta}$, it can be observed that in the case referred, $\frac{C}{L} \le P_\theta$, which implies that

$$q^{**} < 1.$$

This leaves:

If $0 \leq q \leq q^{**} \Rightarrow$ The optimum choice is always to protect.

If $q^{**} < q \leq 1 \Rightarrow$ The optimum choice is: $\begin{cases} \text{To protect}, & if\ Z = 1 \\ \text{Not to protect}, & if\ Z = 0 \end{cases}$

It can be obtained:

$$E(q) = \begin{cases} C, & if\ 0 \leq q \leq q^{**} \\ CP_\theta + LP_0(1 - P_\theta), & if\ q^{**} < q \leq 1 \end{cases}$$

Finally,

$$V(q) = E(0) - E(q) = \begin{cases} 0, & if\ 0 \leq q \leq q^{**} \\ C - CP_\theta - L(1 - P_\theta)(1 - q)P_\theta, & if\ q^{**} < q \leq 1 \end{cases}.$$

4.2.2 Cost-Loss Ratio Situation Model. Dynamic Case

Many of the climate-related decisions must be overtaken repeatedly over a period of time or a sequence of situations. This is the case of protecting crops, a decision that must be taken in a daily basis during a certain period of the year when frosts are likely.

When decisions to be taken at a specific point are not temporally independent, this is, when past weather conditions and choices affect present decisions, the successive application of static models turns to be an inadequate method. These cases require dynamic models that take into account the interrelation of those decisions along time.

The cost-loss model for dynamic use has been studied in works like Katz and Murphy (1997), Murphy et al. (1985), Katz and Murphy (1990), and Katz (1993). These studies cover both the cases of finite and infinite time horizons. These dynamic models take the standard Cost-Loss Ratio Situation as starting point. Nevertheless, none of the cases is able to reach the analytic expression of the expected spendingand, therefore, the value of the information.

The problem is presented in a similar frame as the static model's, with the exception that the decision to protect or not to is taken during N periods when the crop remains as active.

In order to illustrate the need for a dynamic model, Table 4.3 shows the losses expected of r a two-period case (N = 2).

As seen in the table, a static model, which optimises the results for each period, implies that short-term strategies are taken that do not optimise long term accumulated results. Strategy (ii) for example, is inferior than strategy (iii), as results are worse for all circumstances, even if both imply the protection in only one period. If the decision to protect is taken in the second period, the probability of suffering a loss L, turns equal to cero. If the loss would have occurred during period 1, the possibility of protecting during period 2 would not exist, which would diminish the

Table 4.3 Matrix of payments for the case where N = 2

S. no.	Strategy		Expected payment		
	1st period	2nd period	1st period	2nd period	Total
(i)	Protect	Protect	C	C	$2C$
(ii)	Protect	Not protect	C	$P_\theta L$	$C + P_\theta L$
(iii)	Not protect	Protect	$P_\theta L$	$(1 - P_\theta)C$	$C + P_\theta(L - C)$
(iv)	Not protect	Not protect	$P_\theta L$	$(1 - P_\theta)\, P_\theta L$	$(2 - P_\theta)\, P_\theta L$

cost. Therefore, the expected results are better than those associated to strategy (ii), where there exists a possibility that, while having protected the crop in period 1 a loss emerges in period 2. The cost of protecting during period 1 must also be added to this sum, even if this would have turned out to be ineffective.

However, once period 2 is reached, the optimal action is the same as the one associated to the static model, i.e., it is the optimal choice to protect if $P_\theta > \frac{C}{L}$.

For the case there the number of periods N is much higher than 2, the counting is tedious. Therefore, in order to solve the question, a tool for stochastic dynamic programming is used, often using the methodology of reverse induction (in several occasions only numeric solution is possible).

Let N ne a finite number of periods:

$E_N(q)$: the minimum expected spending for the N periods with a quality q.

When only climatic information is available, $q = 0$. Therefore,

$E_N(0)$: the minimum expected spending with climatic information.

Expected spending with climatic information:

The minimum expected spending for the last period (N = 1, due to the inverse process used) for the case with climatic information is given by:

$E_1 = Min\{C, P_\theta L\}$, as the last period decision is identical to the static case.

Starting from that point, the expected spending from the previous period to the end would be expressed as:

$$E_2(0) = Min\{C + E_1(0), P_\theta L + (1 - P_\theta) \cdot E_1(0)\}$$

This is repeated until a backwards generalisation is achieved and the first period can be reached. This would show the expected spending for the N periods taking only climatic information into account:

$$E_N(0) = Min\{C + E_{N-1}(0), P_\theta L + (1 - P_\theta)E_{n-1}(0)\}.$$

Murphy et al. (1985) consider the numeric solving for cases where the number of periods is between 2 and 16, and they describe the optimum policy that minimises the spending throughout those N periods:

- Do not protect the first $N - K$ occasions
- Protect the last K occasions.

Where K is a constant dependent on the loss, costs of protecting and the number of periods.

4.3 Conclusions and Discussion

While agriculture has lost an important share of its weight in the economies of developed countries, and while advances in agrarian technologies have allowed for more resistant and resilient crops, production of food and other goods derived from agriculture still are dependent of climatological conditions in a worldwide context. In a background affected by changes in climate, meteorological predictions may gain further relevance (Fraisse et al. 2006). It is expected that climate change carries serious damages to the agriculture systems in some countries, though the potential impacts in others are unclear yet or could be ambiguous across subsectors. In both cases, uncertainties may have a negative impact over agrarian production.

Another relevant issue could be the dissemination of the knowledge gained through research in order to transform it in practical measures (Bert et al. 2006; Goddard et al. 2010). As previously mentioned, the difference between normative and positive approaches is determined by the existing differences between what is done and what should be done. This may be due to agents operating in a non-rational manner or due to lack of information. The analysis of how information is assimilated leads to a different focus, such as that taken by Marx et al. (2007). Personal experiences and circumstances could modulate perceptions over probabilities in a way that could be difficult to model.

Risk aversion may play a vital role in the differences between these approaches. This is an issue to be considered in future approaches, particularly when normative and positive approaches have to be altogether addressed. Risk aversion is an issue asymmetrically affecting smallholders and big landowners. It can be of high relevance when addressing poor farmers that could experience high losses derived from meteorological phenomena, but also from erred choices based in uncertainties in meteorological prediction. This would lead to the study of agricultural insurance's impact over these farmers (Skees et al. 2008; Kimengsi and Azibo 2015), and therefore the discussion would also incorporate moral hazard. The question in this case would be whether farmers will be less willing to profit from meteorological information when agricultural insurances are available. This scenario would imply that a portion of what is gained from advancements in meteorological information availability and accuracy.

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Chapter 5
Participatory Process: Approaches for Assessing Farmer Behavior Towards Adopting Climate Change Adaptation Strategies in Sub-Saharan Africa

Silvestre García de Jalón

5.1 Introduction

Agriculture has demonstrated throughout history a great ability to adapt to changing conditions. However, currently Sub-Saharan agriculture is also expected to face other relevant challenges such as promoting sustainable agriculture, minimising GHG emissions, and meeting growing food and environmental conservation demands. Implementing adaptation strategies at the farm level is the most direct way for farmers to avoid or reduce potential damages associated to climate change (Field et al. 2014). There are numerous studies that identify a wide variety of adaptation options at the farm level that can reduce potential damages (e.g. Smit and Skinner 2002; Nzuma et al. 2010; Niggli et al. 2009; Field et al. 2014). However, the implementation of adaptation options is affected by biophysical, economic and social barriers. Thus opportunities, constraints and limits to adaptation have recently received much attention within both academic and policymaking spheres (Jones and Boyd 2011; Moser and Ekstrom 2010; Field et al. 2014).

Farm optimisation models have demonstrated that potential adoption of adaptation measures does not always coincide with actual adoption (Adger et al. 2009). This is exemplified with the fact that actual adoption of no-regret and win-win options is considerably lower than estimates of potential adoption. This develops the idea that there are other factors, such as individual behaviour that considerably influence final adoption of measures. In this context, various studies have recently demonstrated the determining role that behavioural barriers can play on the uptake of actions against climate change (e.g. Le Dang et al. 2014). Uncertainty associated with climate change predictions leads to hesitancy in adopting actions in which behavioural barriers could

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increase or prolong this situation of indecision. Climate change scepticism and lack of concern are also very important behavioural barriers caused by the uncertainty (Lorenzoni et al. 2007).

In the last decade there has been growing interest in societal perceptions of climate change and numerous surveys have been conducted to explore societal attitudes and behaviour towards climate change at different scales (e.g. World Wide Views 2009; Abebe et al. 2013; Deressa et al. 2009). Moreover, principles of social and environmental psychology and behavioural economics have been recently used as a basis for research on farmer behaviour towards adoption of climate change actions. Behavioural theories and models on farm decision making aim to identify the reasons why adoption of actions against climate change is not as expected, and how farmer behaviour could be influenced in order to encourage uptake of recommended options. The identification of determinants of adoption may assist policy makers to better comprehend interrelationships among these factors to aid them in policy design (OECD 2012). For this reason, recently a large body of literature has tried to analyse the influence of both psychological and socio-economic factors in order to help to develop policies aiming at motivating or encouraging adoption of climate change actions (Wreford et al. 2010).

Policy instruments can employ incentives/disincentives to influence adoption of actions against climate change in Sub-Saharan Africa (OECD 2012). Agricultural policy instruments can include market mechanisms and price signals; microfinance; insurance instruments; and research and development incentives (Fankhauser et al. 2008). The Articles of the Framework Convention on Climate change (Adger et al. 2006) claimed that adaptation policies should prioritise the most vulnerable regions as it is the basis for deriving potential international transfers to developing countries. Thereby understanding of how the adaptive capacity of societal actors and natural systems influences the potential for adaptation is crucial for successfully developing policies to tackle risks associated with climate change.

For numerous governments adaptation to climate change is now a mainstream concern (Wreford et al. 2010). In Africa, several policies and programmes have also been designed within the context of adaptation (AAP 2013; Beddington et al. 2012). The main objective of adaptation policies and programmes in Africa frequently were to increase household food security, to reduce poverty through improved livelihoods, and to facilitate integration of climate change adaptation into policies related to disaster management and sustainable development (IFAD 2013). Adaptation policies planned on global or regional scales will ultimately proceed on a decision-making process at the local, farm or individual level. Thus understanding farm-level decision-making processes and behaviour is crucial to successfully implement climate change policies (OECD 2012).

The remaining sections are presented as follows. The next three sections describe analytical approaches that can be used to assess the uptake of climate change adaptation strategies in Sub-Saharan agriculture. Each section corresponds to a group of approaches according to the spatial scale: (i) approaches that aim to evaluate adoption at the farm-level and understanding the drivers of farmer choices at the individual level, (ii) approaches that aim to up-scale adoption from farm to regional scale—bottom-up approaches and, (iii) approaches that aim to refine regional estimates of adoption—top-down approaches. A case study in each group of approaches has been presented to show the applicability of the methodology. The last section shows the conclusions of the chapter.

5.2 Approaches Assessing Farmer Choices at Individual or Farm Scale

The success or failure of policy interventions is often ultimately determined by decisions made at the farm-level. Thus understanding farmer perceptions and choices can be essential to design appropriate policies that can foster the uptake of adaptation options to climate change.

5.2.1 Data Collection Methods

There exists a wide range of approaches to qualitatively and quantitatively collect data for assessing farmer behaviour and drivers of adaptation. The choice of method depends on the expected quality of the collected data, estimated costs, spatial scales, predicted non-response rates, expected level of measure errors, and length of the data collection period (Lyberg and Kasprzyk 1991).

The most popular data collection techniques for assessing farmer choices in regards to adoption of actions related to climate change are surveys, focus group discussions, stakeholder participatory workshops, interviews (face-to-face, telephone, mail, or e-mail), direct observations, and secondary data sources or archival data.

On the one hand, surveys can be used for gathering both qualitative and quantitative data. They can be administrated as part of an experiment, a mailed survey or questionnaire, a semi-structured interview, a Web survey, or a questionnaire. On the other hand, focus group discussions, stakeholder workshops and interviews are typically used for gathering qualitative data. Despite the information obtained with these qualitative techniques usually being not measureable or quantifiable frequently the information is richer and has a deeper insight into the phenomenon under study than with surveys.

Secondary data sources or archival data includes public and private databases and review of previous case studies. Typical databases used in agriculture are Faostat, Worldbank, Aquastat, GeoNetwork, WorldClim, FADN, etc. Finally review of previous case studies and meta-analyses can be employed for obtaining qualitative and quantitative data.

5.2.2 Data Analysis Methods

There is a wide range of analytical methods that can be used for evaluating farmer choices and their drivers. The most important ones can be classified as statistical and qualitative approaches:

Statistical approaches: Statistical methods include univariate analysis (such as analysis of single-variable distributions), bivariate analysis, and multivariate analysis. Multivariate analysis refers to all statistical methods that simultaneously analyse multiple measurements on each individual or object under investigation (Hair et al. 2006). Often they are extensions of univariate and bivariate analysis. The three most commonly used methods are General linear model, Generalized linear model and Structural equation modelling.

- General linear model is widely used for assessing the effect of several predictors on one or more continuous dependent variables. Methods such as 't-test', 'ANOVA', 'MANOVA' are based on general linear models.
- Generalized linear model is an extension of the general linear model that allows response variables having error distribution models other than a normal distribution such as discrete dependent variables. It includes linear regression, logistic regression and Poisson regression. Numerous studies have used generalized linear models to assess the influence of drivers of adoption of adaptation measures (e.g. Gebrehiwot and van der Veen 2013; Bryan et al. 2013; Silvestri et al. 2012; Deressa et al. 2009). These studies usually employ logit and probit models for measuring the influence of socio-economic factors on a binary dependent variable which represent the adoption of a determined adaptation measure.
- Structural equation modelling (SEM) technique is widely used for assessing latent structures from measured manifest variables. It has used for analysing people behaviour towards climate change and support for implementing actions (Islam et al. 2013; Tikir and Lehmann 2011).

Qualitative approaches: These allow direct elicitation of farmer behaviour, barriers, and intention of adoption. Qualitative methods can include basic methods such as Participatory Rural Appraisal, but also other methods to elicit narrative statements related to farmer behaviour towards climate change (e.g. Q-methodology) (Cross et al. 2012). These approaches allow the exploration of decision-making processes at the farm level on relation to adoption of adaptation under a range of scenarios (Le Dang et al. 2014; Moran et al. 2013).

Deterministic farm-scale models and approaches to evaluate land use change: Farm-scale models can incorporate the output from biophysical models such as changes in crop yields into economic models to provide the basis for profit maximisation at the farm level (van Ittersuma et al. 2008). This objective is one of many that can be measured with optimisation programming at the farm-level, which is most appropriate for understanding the cost-effectiveness of implementing adaptation measures. These models can take exogenous price shifts (e.g. caused by climate change), technical relationships between inputs and outputs and a set of constraints.

As the model results can be used to compare scenarios of interventions and its impact across farm-level resource use and inputs they also can estimate potential uptake of adaptation measures (Moran et al. 2013). The attraction of this approach is that estimates of potential uptake of adaptation measures can be compared with actual uptake. Thus, this approach allows assessing the role of behavioural barriers along with other types of constraints towards adoption. These optimisation models can also be used to analyse the optimal combination of land uses or adaptation options under different biophysical or socio-economic scenarios. This allows assessing under different behavioural attitudes towards climate change, optimal combinations of adaptation options and land uses.

Agent based models: Agent-based models are a helpful tool to investigate complex dynamics in coupled humane natural systems (Müller et al. 2014). Recently they have been used to evaluate farmer adoption of adaptation measures at the farm level as well as peer effect in the diffusion of adoption among farmers. Often, the estimation of rational optimisation models does not correspond to actual estimates of adoption due to a lack of farmer behavioural information such as social limits to adaptation (Adger et al. 2009; Le Dang et al. 2014). Agent-based models allow relaxing the more deterministic assumptions inherent in most optimisation models and to use less restrictive rules to codify behaviours towards particular policy interventions such as fostering adoption of climate change actions.

5.2.3 Limitations

The main limitation of the approaches that assess farmer choices at the individual level is the fact that the results cannot easily extrapolated for other areas since different biophysical or socio-economic contexts can change the drivers of farmer choices. In the case of qualitative approaches, the lack of quantitative measurements hinders the comparison across different areas. In the case of statistical approaches, the results are subject to the statistically significance and numerous studies only report those factors that had a significant effect on adoption. However, farmer choices are often much more complicated than a regression analysis since there can be numerous factors that cannot be measured but play a key role on determining the behaviour or the irrationality of decision making processes is not fully considered. Another limitation is the need of a representative sample. Small sample sizes can lead to biased estimations.

5.2.4 *Case Study: Behavioural Barriers in Response to Climate Change in Agricultural Communities: An Example from Kenya*

For further information about this study please see García de Jalón et al. (2015).

5.2.4.1 Overview

This case study presents an approach to evaluate farmers' behavioural barriers and their main drivers in order to include behavioural constraints in the modelling frameworks. The location of the case study is in various villages of Makueni County in the Eastern Province of Kenya (Fig. 5.1). Makueni covers an area of around 8000 km^2 with a population of around 884,527 in 2015. Most households derive their livelihoods mainly from crop production and trade, livestock keeping and sale, as well as from low-income non-farm activities such as unskilled casual jobs, business, paid employment, remittances and pensions.

5.2.4.2 Data Collection

Focus group discussions and a survey were conducted to collect qualitative and quantitative data, respectively.

Focus group discussions

The main goal of the focus group discussions was to conduct an exploratory analysis of the perceptions of local farmers about climate change. Furthermore, the focus

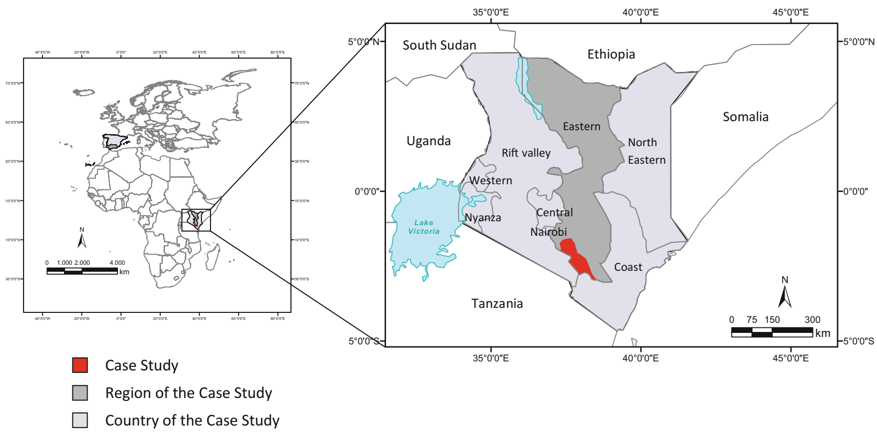

Fig. 5.1 Location of Makueni case study

groups focused on the barriers that could limit adoption of farm-management practices related to mitigation and adaptation to climate change. Focus group discussions also aimed to provide information to design the questionnaire and to identify the most relevant barriers amongst local smallholder farmers.

Three focus group discussions consisting of six to twelve participants per group were implemented in 2013. One group was composed by solely male farmers, another one by female farmers and the third one by agricultural technical advisors. The focus groups were conducted separately by gender due to cultural reasons. It was assumed that females would tend not to participate as much in the debates if males were present. Focus group discussions were conducted in Kamba language with the farmers and in English with the agricultural advisors. All focus group discussions were audio-recorded and transcribed verbatim. In each focus group, a moderator, translator and note taker were hired.

Survey implementation

The survey aimed to gather information on farmers' climate change concern, behavioural barriers to mitigation and adaptation, concern and attitudes towards the environment, institutions and policy, and demographic and farm characteristics in Makueni.

A survey of 133 farmers in the main villages of Makueni was conducted in 2013. Responses to the questions were measured using statements and five-point Likert scale (i.e. 1 = totally disagree; 5 = totally agree). The use of Likert scales allowed transforming the responses into quantitative data and to apply statistical methods adapted to interval data (Robson 1993; Greiner et al. 2009).

5.2.4.3 Data Analysis

Identifying a typology of behavioural barriers

A typology of behavioural barriers was identified by the use of principal component analysis technique. This technique allowed the reduction of a large number of questionnaire statements to a more concise number of general dimensions for further analysis. Thus the segmentation of the behavioural barriers was conducted by three separate principal component analyses (Comrey and Lee 1992) focussing on climate change scepticism, denial of self-responsibility, and attitudes to behavioural change.

In the principal component analysis a Varimax rotation was conducted. Those factors with eigenvalues higher than 1 were retained to form the behavioural barriers. These factors were defined by questionnaire statements for which principal component analysis factor loadings were greater than 0.45 (Comrey and Lee 1992). Since the loadings were correlation coefficients between statements and factors they indicated the contribution of a statement in defining the factor. Thus respondents' scores in each factor (i.e. farmer's behavioural barriers) was measured through the weighted sum of the scores on the questionnaire statements according to the loadings of those factors with values higher than 0.45. Subsequently, a Kaiser-Meyer-Olkin test (KMO test) was calculated to demonstrate the validity of principal component analysis for the data (Kaiser 1974), and for the factors with multiple questionnaire statements a Cronbach's alpha test was also computed to gauge their reliability.

Assessing the influence of socio-economic determinants

The influence of the determinants on displaying the identified behavioural barriers was analysed by a binary Logit model. In order to compute the binary Logit model the distribution of the scores was transformed into a binomial distribution. Equation (5.1) describes the Logit model of a binomial distribution B(·),

$$\pi_i = \wedge\left[x_i'\beta\right] \tag{5.1}$$

where $\wedge[\cdot]$ denotes the univariate logistic cumulative distribution function which is shown in Eq. (5.2),

$$\wedge[\cdot] = \frac{1}{1 + \mathrm{e}^{-x_i'\beta}} \tag{5.2}$$

where x_i were the independent variables and β the estimated coefficients. πi indicated the probability of success, which was the probability of displaying a determined behavioural barrier conditioned to the independent variables for each farmer.

The dependent variables were dummy variables taking the value of 1 if farmer i had a determined behavioural barrier and 0 otherwise. The independent variables were the socio-economic determinants of the behavioural barriers which were basically formed by demographic and farm characteristics (Table 5.1). Marginal effects were calculated for ease of interpretation of the logistic regression results. Thereby the coefficients of the regressions show the expected change in the probability that farmers displayed a determined behavioural barrier in relation to the adoption of mitigation and adaptation measures.

5.2.4.4 Results: A Typology of Behavioural Barriers and Influence of Socio-Demographic Determinants

The principal analysis component allowed identifying a typology of behavioural barriers and measuring its frequency. Figure 5.2 shows the frequency distribution of the barriers and ranges them from personal beliefs to knowledge. The spectrum also reflects the complexity to overcome the barriers through policy intervention. The distribution was estimated from the information obtained in the focus group discussions among agricultural technical advisors, a literature review, and discussions amongst the authors.

The marginal effect of the estimated coefficients in the logistic regressions were used to measure the expected changes in the probability of displaying a behavioural barrier, given a unit change in an independent variable from the mean value, maintaining constant the rest of the variables (see Table 5.1).

Table 5.1 Determinants of farmers' behavioural barriers to adoption of climate change actions and marginal effects in Makueni, Kenya

Variable	Scepticism	Lack of concern	Fatalism and helplessness	Externalising responsibility	Blaming lack of adequate policies	Reluctance to change	Lack of knowledge to change
Gender (male)	0.133**	−0.037	−0.021	−0.082	0.011	−0.027	0.022
Age	−0.002	−0.006	−0.003	0.000	0.005	−0.001	−0.009***
Education	−0.079*	−0.024	−0.073	0.008	0.036	−0.160**	−0.079*
Land ownership	−0.041	0.303	0.069	−0.297	0.258	−0.129	0.140
Livestock ownership	0.003	−0.013	0.033	−0.021	−0.030	0.032	−0.007
Farm size	0.000	0.017	−0.012	0.012	0.017	−0.049 **	0.007
Members on-farm	0.021**	−0.021	0.001	−0.037	0.004	0.027	−0.001
Members off-farm	0.009	−0.001	0.020	−0.022	−0.024	0.030	0.038*
Credit access		−0.064	0.053	0.015	−0.067	0.066	−0.076
Food aid	0.115*	−0.023	−0.058	0.032	−0.116	−0.001	−0.202***
Access to weather forecast		0.143	−0.341**		−0.359*	−0.359***	0.007
N	133	110	110	133	133	110	110

Adapted from García de Jalón et al. (2015)
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

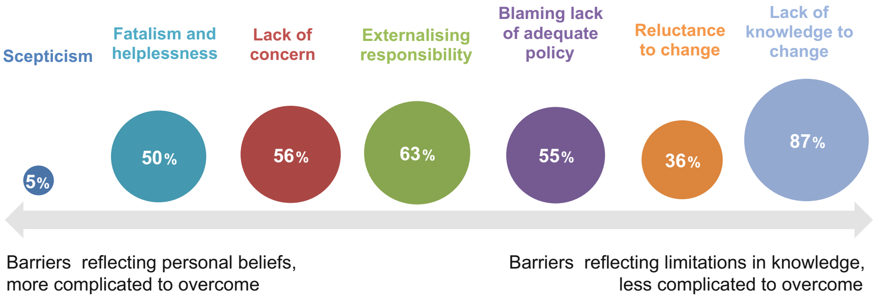

Fig. 5.2 Percentage of respondents displaying the behavioural barriers (proportion represented by area) in Makueni case study. The bidirectional arrow describes the barriers more influenced by personal beliefs and by personal knowledge as well as the difficulty in overcoming the barriers through policy intervention. *Source* García de Jalón et al. (2015)

5.2.4.5 Lessons Learned

In Makueni case study, the results from the focus group discussions demonstrated that both farmers and agricultural technical advisors were notably aware of climate change impacts, in particular changes in the annual distribution of precipitation and increases in the occurrence of droughts.

The survey results helped identify a typology of behavioural barriers among farmers and measure their frequency distribution. The results indicated that whilst there is awareness of climate change impacts among farmers, the lack of knowledge to change farm-management practices seemed to be the most frequent barrier to adoption of mitigation and adaptation strategies.

The survey results also measured the influence of socio-economic determinants on the identified behavioural barriers. This was measured by the marginal effects analysis. The marginal effect analysis showed that receiving climate information was the most influential determinant of displaying the majority of behavioural barriers, followed by education, and receiving food aid.

5.3 Approaches to Up-scale the Uptake of Farm-level Adaptation Strategies at Regional Scale

The previous section described some approaches to assess farmer decisions. These decisions at the farm level can determine the success of policy measures that aim to foster the uptake of adaptation strategies to climate change. However, understanding how a determined practice is adopted at higher spatial scales such as Sub-Saharan Africa can help to identify potential areas where policy interventions could be more cost effective. Thus up-scaling farm-level adoption can be necessary to assess how recommended practices are or will be adopted by farmers. This section focuses on approaches to collect and analyse data with the purpose of up-scaling the uptake of farm-level adaptation strategies to climate change.

5.3.1 Data Collection Methods

In order to up-scale the uptake of adaptation strategies to climate change secondary data sources or archival data from public and private databases are commonly used. Typical databases used in agriculture in Sub-Saharan Africa are Faostat, Worldbank, Aquastat, GeoNetwork, WorldClim, etc. Furthermore, a review of previous case studies can be used to assess adoption and drivers of adoption at regional scale. Meta-analyses can be employed for obtaining qualitative and quantitative data.

5.3.2 Data Analysis Methods

There are various groups of approaches that can be used to up-scale farm level adoption of adaptation strategies to climate change. These approaches can be classified in three main groups: (i) composite indicators, (ii) meta-analyses and, (iii) deterministic farm-scale models.

Composite indicators: These are increasingly recognised as a useful tool in policy analysis and public communication. Composite indicators provide simple comparisons of regions or countries that can be used to illustrate complex and sometimes elusive issues in wide-ranging fields such as environment, economy, society or technological development (OECD 2008).

Numerous studies have demonstrated that socio-economic characteristics of farm and farmers considerably influence final adoption of farm-level adaptation measures (Deressa et al. 2009; Bryan et al. 2013; Silvestri et al. 2012). These socio-economic characteristics can be estimated at the regional or country level by the use of indicators from public and private databases. Thus composite indicators can be a very helpful tool to evaluate where adaptation measures are more or less likely to be implemented. Composite indicators have been widely used for evaluating regional vulnerability of socio-ecological systems to impacts associated to climate change (e.g. Thornton et al. 2006; Brooks et al. 2005).

Meta-analysis: This technique refers to methods that focus on contrasting and combining results from different studies and can be used for obtaining both quantitative and qualitative data. Meta-analysis attempts to identify patterns among study results, sources of disagreement among those results, or other interesting relationships among multiple studies (Greenland and Longnecker 1992). By meta-regressions the influence of drivers of adoption of farm-level adaptation measures can be assessed across various case studies by measuring the effect size of common independent variables (Baumgart-Getz et al. 2012; Knowler and Bradshaw 2007). The study by Baumgart-Getz et al. (2012) uses a meta-analysis technique to quantitatively assess the influence of socio-economic characteristics of farmers on adoption of best management practices. The authors summarized the adoption literature and identified those variables that have the largest impact on adoption.

General Equilibrium models in the agricultural sector: These models can be used to estimate how the economy of the agricultural sector might react to changes in policy, technology or other external factors. These models can be based on the output of farm-scale models that provide the basis for profit maximisation at the farm level (van Ittersuma et al. 2008). General Equilibrium models can take exogenous price shifts (e.g. caused by climate change), technical relationships between inputs and outputs and a set of constraints.

Agent based models: Agent based models can be used to up-scale adoption at regional scale. They are particularly interesting to simulate the peer effect in the diffusion of adoption among farmers. Frequently, the estimation of rational optimisation models does not correspond to actual estimates of adoption due to a lack of farmer behavioural information such as social limits to adaptation (Adger et al.

2009). Agent-based models allow relaxing the more deterministic assumptions inherent in most optimisation models and to use less restrictive rules to codify behaviours towards particular policy interventions such as fostering adoption of climate change actions.

5.3.3 Limitations

Up-scaling adoption at higher spatial scales can be subject to various limitations. As a rule of thumb, it can be assumed that the higher the spatial scale the lower the accuracy of the adoption estimates. Thus there should be a balance between the spatial coverage and the accuracy of the estimations. In the case of meta-analyses, these approaches can be limited by the fact that the studies used in the analysis often evaluate different types of farm-level adaptation strategies and regions in Africa. Thereby some important regional effects of case studies and different exploratory variables for distinct adaptation strategies cannot be considered in the selection of variables. This limitation sometimes can be avoided with a greater sample of case studies which could allow classifying regions and adaptation strategies into more homogenous groups. In the case of composite indexes and regional or global models such as general equilibrium models and agent based models the main limitation can be the lack of high-resolution data. Particularly in Sub-Saharan Africa, available data often cannot be disaggregated at scales lower than the national level and sometimes there is no availability of completed data in datasets. This may lead to an oversimplification of the input data. As local characteristics of the biophysical and socio-economic contexts can determine adoption the up-scale for certain geographical areas can be rather inaccurate. Another limitation of composite indexes is the weighting and aggregation approaches. OECD (2008) highlighted that there exists no consensus on the selection of weights in composite indexes in the literature. For this reason, assessing the robustness of the composite index by a sensitivity analysis is recommendable. The sensitivity analysis can assess the effect of the utilised weighting and aggregation approaches on the results. Notwithstanding these limitations, the regional estimation of farm-level adoption of adaptation is an issue of international interest and can help policy makers to identify those regions where smallholder farmers are less likely to adapt to climate change and, consequently, to suffer more impacts.

5.3.4 Case Study: A Composite Index to Up-scale the Uptake of Adaptation Strategies in Africa

For further information about this study please see García de Jalón et al. (2016).

5.3.4.1 Overview

This case study presents a composite index of potential adoption of farm-level adaptation strategies based on a comprehensive review of past research. The composite index assesses the likelihood of adopting farm-level adaptation strategies for Africa. The methodological process of the case study can be summarised in six steps:

- selection of case studies in Africa and published in peer-review journals,
- identifying independent variables that regularly explain adoption,
- grouping these independent variables into components,
- selection of proxies at national level that define each component of potential adoption,
- estimation of regional likelihood of adoption of farm-level adaptation strategies through the calculation of a composite index,
- analysing limitations and sources of uncertainty of the composite index by a sensitivity analysis (Fig. 5.3).

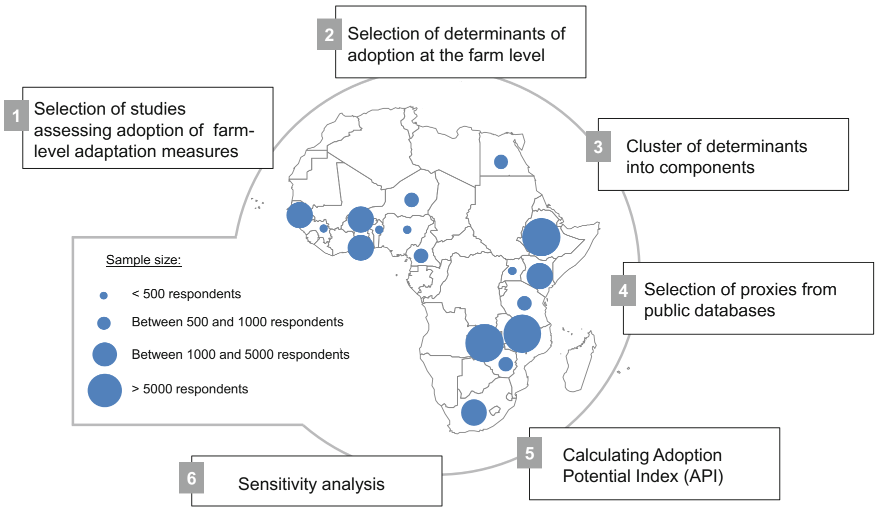

Fig. 5.3 Methodological process for assessing the probability of adoption of farm-level adaptation strategies to climate change through the estimation of the Potential Adoption Index (API) in Africa. The size of the dots indicates the sample size of the econometric analysis for the 17 African countries where the case studies where implemented

5.3.4.2 Data Collection

In this case study, the collected data was obtained from past research and public databases. The synthesis of past research was used for the selection of proxies. In a composite index, the selection of proxies should be based on the analytical soundness, measurability, and relevance to the phenomenon being measured and their relationship to these phenomena (OECD 2008). 42 case studies published in peer-review journals were reviewed and synthesized to identify independent variables that regularly explain adoption. Thus the identified variables could be used to develop a composite index of adaptation adoption. The 42 studies included 100 analyses (mainly econometric regressions) of socio-economic factors that influence adoption of farm-level adaptation strategies.

The independent variables of the 100 analyses were classified into components. As the case studies were carried out at the farm level and within the African continent the aggregation into components was quite consistent and reliable. By using public databases, proxies of the components were used to calculate the composite index.

The selection of proxies was based on three key criteria: (i) the variable had to represent a quantitative or qualitative aspect of both adoption of adaptation and the identified components, (ii) data needed to be available in public databases, and (iii) each variable had to have at least fifty percent of the countries without missing data (OECD 2008; Naumann et al. 2014). The use of public databases ensured that the final result could be validated, reproduced and improved with new data (Vincent 2004; Naumann et al. 2014). Besides, the divergence of independent variables towards a positive and significant influence on adoption was also considered to select proxies of the components.

Several countries presented significant amount of missing data. For those countries with missing data the values were completed from secondary sources and from neighbouring countries. Vincent (2004) recommends the substitution for missing values when it is unavoidable, given the variable data availability, and points out the risk of basing these substitutions on subjectivity alone. Vincent (2004) claims that the only solution is to make such choices transparent, in order to enable effective critical evaluation of the robustness of the index.

5.3.4.3 Data Analysis

Calculating the Adoption Potential Index (API) of farm-level adaptation strategies

Once all data have been collected, as most proxies had different measurement units the variables needed to be normalised. This normalisation allows direct comparison between results among countries and or regions. Normalisation was carried out taking into account the minimum and maximum value of each proxy across all countries. Thereby it was guaranteed that all proxies ranged between 0 and 1 (Naumann et al. 2014). For those proxies with a positive correlation to the estimated index, the normalized value was estimated according to the following linear transformation:

$$Z_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{5.3}$$

where X_i was the variable value for country i, X_{min} and X_{max} the minimum and maximum value across all countries i. For those proxies with a negative and significant correlation with the estimated composite index, the normalised values were reversed. Thereby, all normalized proxies (Z_i) ranged between 0 (lowest adoption rate of farm-level adaptation) and 1 (highest adoption rate).

For each country, any of the j (j = 1, …, 7) components (C) were calculated as the mean of the proxies Z_i that define each component (Eq. 5.4). Equation (5.5) indicates how the API of each country was calculated as a weighted aggregation of the components.

$$C_j = \frac{1}{n}\sum_{j=1}^{n} Z_j \tag{5.4}$$

$$API_i = \sum_{j=1}^{7} W_j C_{i,j} \tag{5.5}$$

where W_j were the weights assigned for the j component (with $\sum w_j = 1$) and $C_{i,j}$ were the components for each country. In this way, the API scores were the relative index value of a country with respect to the rest of the countries. These values ranged from 0 to 1, where 0 represented the lowest likelihood of adoption of farm-level adaptation strategies and 1 is associated with the highest likelihood.

Sensitivity and sources of uncertainty

After calculating the composite index it was necessary to test the robustness and stability of the weights since no perfect weighting and aggregation convention exists for composite indexes (Arrow 1963). Three different weighting schemes were used to test the influence of weighting on the composite index: (i) equal weights among components (equal weights), (ii) weighting scheme according to the number of proxies in each component (proportional weights), and (iii) random weights (using the Monte Carlo method with 1000 simulations).

Sensitivity analysis is often implement to evaluate the robustness and validity of a composite index (OECD 2008). Sensitivity analysis assesses how uncertainty in the input factors (variables, and aggregation) propagates through the structure of the index. In this case study, the sensitivity analysis was performed by Monte Carlo experiments to measure the contribution of any individual source of uncertainty to the output variance. This approach was based on multiple evaluations of the model with different weighting and aggregation schemes that generated various probabilistic density functions of model outputs (Naumann et al. 2014). Moreover, the robustness of the index was assessed by the stability of the country rankings assigned by the index value in the sensitivity analysis. Thus, the shift in country rankings reflected the uncertainty associated to each input factor.

Two main assumptions were tested in the sensitivity analysis: (i) the selection of the weights in the aggregation of components, and (ii) the possibility that proxies were not correctly measured. The first assumption was tested by analysing the effect on the composite index of all countries when assigning random weights to the components. 1000 repetitions were done for the values of the components weights to calculate the composite index. The second assumption (sensitivity of components), evaluated the effect on the composite index when selecting random values for one component. A random value was assigned to one component in each experiment. For each weighting scheme, seven experiments of 1000 repetitions were computed. Thereby, in total 21,000 repetitions were conducted to assess the sensitivity of the index to the component values.

5.3.4.4 Results: Selection of Variables, Estimating Potential Adoption and Sensitivity Analysis

Those variables that were most frequently used to analyse adoption were identified in the review of past research. 26 variables were selected from a database containing 935 variables in 100 econometric analyses. Those variables that were not frequently used were excluded from the analysis. This was because it was assumed that they would probably not show a pattern across empirical studies (Knowler and Bradshaw 2007). Given the similarities in variables used across the 100 analyses, aggregation was undertaken into seven components in terms of financial resources, infrastructure and technology, human capital, dependence on agriculture, food security, social interaction and governance, and attitudes towards the environment.

Proxies from national-level public databases were selected based on the previous identification of variables and components in the review of past research. 28 proxies were selected and aggregated in the aforementioned seven components.

The separate value of the components helps understand the source of the API. The map by deciles of the API is shown in Fig. 5.4. The map showed that Northern Africa had the highest likelihood of adoption of farm-level adaptation strategies followed by Southern Africa, Western Africa, Central Africa, and lastly Eastern Africa.

5.3.4.5 Lessons Learned

This case study presents an approach that allowed seeing the whole picture of adoption of farm-level adaptation strategies in Africa. The case study introduced a novel methodology, based on recent research data rather than subjective identification of proxies. The approach provided a transparent procedure for the estimation of a composite index to measure farm-level adoption of adaptation. It also offered a robust methodology for the identification of regions where smallholder farmers were less

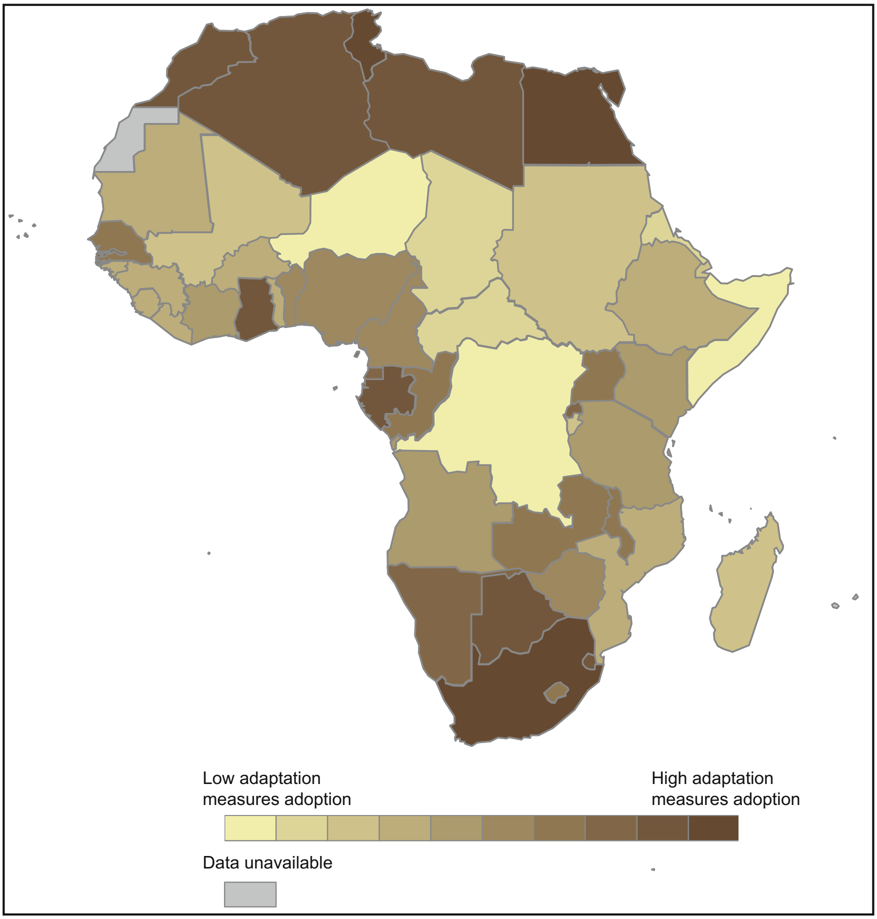

Fig. 5.4 Map by deciles of the Adoption Potential Index (API) in Africa. *Source* García de Jalón et al. (2016)

likely to adopt adaptation strategies. The results of the composite index suggested where there was more potential for improving adoption of adaptation strategies in Africa. The sensitivity analysis conducted to test the weighting schemes and component values showed that the index was reasonably robust and especially appropriate to estimating regional adoption of farm-level adaptation strategies to climate change.

5.4 Approaches to Refine Regional Estimates of Adoption

The estimation of the uptake of climate change adaptation strategies at the regional level can sometimes suffers from a lack of accuracy due to local variability in terms of biophysical and socio-economic aspects. A top-down approach can be used to refine regional estimates of adoption to local or farm level estimates. Thereby, adoption estimates at the regional level can be used to predict adoption of a practice in farm type with determined characteristics. This can be estimated by the use 'fiction' coefficients that refine regional estimates of adoption for different types of farms.

5.4.1 Data Collection Methods

In order to down-scale regional estimates with a higher resolution farm-level data is essential. The survey of the CGIAR Research program on Climate Change, Agriculture and Food Security (CCAFS) is particularly useful to assess drivers of farm-level adoption of numerous practices in Sub-Saharan Africa. CCAFS survey was carried out in 2010 and 2011 and is one of the most reliable farm-level database available across the continent. The survey includes several Sub-Saharan African countries with more than 1500 farm-households. Moreover, the use of other public and private databases can be utilised for quantitative data or indicators.

5.4.2 Data Analysis Methods

The data analysis process is based on the selection of drivers of adoption for the proxies of the evaluated adaptation strategies to climate change. The influence of the drivers of adoption of the selected proxies is assessed by a statistical approach. Mixed models (linear mixed models or generalised linear mixed model) containing both fixed effects and random effects seem to be appropriate where measurements are made on clusters of related statistical units. For instance, in the case of generalised linear mixed model (GLMM), the adoption of the practices is treated as a binary dependent variable (with the value of 1 indicating adoption) and the drivers of adoption of the practices are often used as predictors.

5.4.3 Limitations

These approaches can be an important tool when predicting adoption of a practice when there are no data available or when the estimations may be rather inaccurate because they were calculated at large spatial scales. It is worth highlighting two limitations for taking forward. Firstly, to derive the uptake of the climate change adaptation practices, it is common to select agricultural practices in which adoption is driven by similar determinants. Consequently, this needs to be based on proxies or indicators. Secondly, the potential for adoption of the climate change adaptation practices is usually calculated as the average of the probability of the proxies, assuming the same weight for all proxies. However, proxies can have different weights. A way to solve this issue would be to assign specific weights for the proxies. This could be done by using a survey with main experts and stakeholders. The Analytical Hierarchical Process technique by pairwise comparisons would be very suitable to assign weights according to the opinion of stakeholders and key actors.

5.4.4 Case Study: Assessing Potential for Adoption of Climate Smart Agricultural Practices

For further information about this study please see García de Jalón et al. (2017).

5.4.4.1 Overview

This case study aimed to evaluate the potential of adoption of climate smart agricultural (CSA) practices in Sub-Saharan livestock systems.

By the use of CCAFS survey in nine Sub-Saharan countries, a mixed Logit model was used to assess the influence of socio-economic determinants on adoption and to estimate the probability of adoption. Our results show that there seems to be a stronger influence of physical and financial capitals on adoption is greater than the influence of other capitals. However, the influence of the capitals on adoption varies depending on the evaluated practice. The results of this case study could help refine adoption estimates calculated through global or regional modelling approaches and to provide more detailed information to better target investments in order to foster adoption.

5.4.4.2 Data Collection

Data used in this study were collected from the CCAFS survey of the CGIAR Research program conducted between 2010 and 2011. The survey was carried out across nine different countries of SSA (Burkina Faso, Ghana, Mali, Niger, Senegal, Ethiopia, Kenya, Tanzania, and Uganda). In total the sample includes 1538 farm-households.

5.4.4.3 Data Analysis

Selection of proxies for the climate smart agricultural practices

The selection of the CSA was the first step of the methodological process. The selection was based on agricultural practices that (i) have similar drivers of adoption to our four selected practices, and for which (ii) there are available data to assess the influence of their drivers on adoption. The analytical soundness, measurability, and the relationship between the proxies and the CSA practices was considered in the selection process.

The adoption of the selected proxies was measured as a binary variable which takes the value 1 if the practice was adopted and 0 otherwise.

Selection of determinants of adoption

Subsequently the drivers of adoption for the proxies of the CSA practices were selected. The five types of capital framework (natural, physical, financial, human, and social) were used to classify the determinants. Thus, multiple indicators of the five types of capital were selected.

Assessing the influence of the five types of capital on adoption

A generalised linear mixed model (GLMM) was used to assess the influence of the five types of capital on the adoption of the selected proxies of the CSA practices by the use of CCAFS data.

In the model, the adoption of the practices is treated as a binary dependent variable (with the value of 1 indicating adoption) and the five types of capital are used as predictors. A random intercept Logit model was utilised in which the random effects for each village where the survey had been implemented (80 villages across the nine countries) was considered.

The random intercept Logit model in terms of a latent linear response is described in Eq. (5.6), where only $y_{ij} = I\left(y_{ij}^{*} > 0\right)$ is observed for the latent

$$y_{ij}^{*} = X_{ij}\beta + Z_{ij}U_j + \varepsilon_{ij} \tag{5.6}$$

where y_{ij}^{*} indicated the probability of success (the probability of adopting a determined practice conditioned to the independent variables for each farm). The dependent variables were dummy variables taking the value of 1 if farm i adopted a determined practice and 0 otherwise. X_{ij} were the covariates for the fixed effects (i.e. five capitals) of farm-household i in village j, with regression coefficients (fixed effects) β. Z_{ij} were the covariates corresponding to the random effects and can be used to represent both random intercepts and random coefficients. As our case is a random intercept model, Z_{ij} equals the scalar 1. U_j was the error term for the random effects of the 80 villages which were estimated as variance components. ε_{ij} were the errors distributed as logistic with mean 0 and variance $\pi^{2/3}$ and were independent of U_j.

Defining $\pi_{ij} = Prob\left(adoption_{ij} = 1\right)$, Eq. (5.7) shows the final random intercept Logit model,

$$logit(\pi_{ij}) = \beta_0 + \beta_1 Human_{ij} + \beta_2 Natural_{ij} + \beta_3 Physical_{ij} + \beta_4 Social_{ij} + \beta_5 Financial_{ij} + U_j \quad (5.7)$$

for j = 1, …, 80, with i = 1, …, nj farm-households in village j.

Evaluating potential for adoption of the agricultural practices

Evaluating the potential for adoption of the four CSA practices was the last step of the methodological process. The likelihood of adoption was estimated from the estimated coefficients in the mixed Logit model. Thereby the probability of adoption of each proxy was calculated by substituting the betas ($\beta_0 - \beta_5$) in Eq. (5.7) by the estimated coefficients in the logistic regressions. Lastly, the potential for adoption of each CSA practice was calculated as the average of the estimated probabilities of their respective proxies.

5.4.4.4 Results: Influence of Capitals on Adoption and Potential for Adoption

The results of the estimated coefficients of the mixed logistic regressions are shown in Table 5.2. Except natural capital, all types of capitals seemed to have a positive and significant effect on the adoption of the practi**ces.**

The estimated coefficients of the mixed logistic regressions were used to calculate the likelihood of adoption for each proxy (Eq. 5.7). Then the potential for adoption of the CSA practices was calculated as the average of the probability of the proxies.

The estimated probability of adoption of the four CSA practices by the case study developed in each country is shown in Fig. 5.5. It is important to take into account that the analysis per country did not aim to represent the whole country but the study sites and the differences across the study sites. Overall, the results suggested that the highest probability of adoption can be found in Kenya, Tanzania, Burkina Faso and Ghana. On the contrary, Ethiopia, Mali and Niger present the lowest likelihood of adoption of the four practices.

5.4.4.5 Lessons Learned

This case study evaluated the potential for adoption of four CSA practices across rural communities in sub-Saharan livestock systems. This approach is useful for assessing the potential for adoption of agricultural practices that are not currently being implemented or, because of lack of data adoption, cannot be estimated directly through other approaches. This requires survey data of selected proxies for the practices and calculates probabilities of adoption based on these proxies. Thus the results could represent a first step to more accurately estimate potential for mitigation of greenhouse gas emissions in Sub-Saharan livestock systems.

The method could be used in combination with other approaches that estimate adoption rates. For instance, in order to estimate adoption at large scales, marginal abatement cost curves are used in optimisation models that often maximise net farm-income and are subject to certain constraints such as land and water availability, food demand and greenhouse gas emissions. Thus in order to maximise farm-income optimisation models can suggest full adoption of a practice in a region. This can be due to the fact that the economic profitability of the practice in theory is higher than other practices. However, there are numerous barriers such as lack of knowledge, access to markets or biophysical constraints at the plot level that ultimately determine adoption. Accordingly, by highlighting the heterogeneity in adoption our approach could be used as a 'friction' coefficient in order to refine estimates made by models at large scales. This would be the estimated potential for adoption which would be calculated according to the levels of different capitals in the area of study.

5.5 Conclusions

This chapter presents a framework based on a wide range of approaches in collecting and analyzing data to assess drivers in adopting adaptation strategies to climate change in Sub-Saharan agriculture. The methodological framework analyses adoption of adaptation measures at various spatial scales. The chapter has shown the

Table 5.2 Estimated coefficients of mixed logistic regressions assessing adoption of the climate smart agricultural practices

	Fencing introduced	Fodder storage (e.g. hay, silage)	Growing fodder crops	Improved pastures	Introduced mecha-nized farming	Planting pre-treated/improved seed	Stall keeping introduced	New breed introduced
Human	1.00***	1.01***	0.61**	0.20	1.5***	0.99***	0.25	0.57***
Natural	−0.56	−2.52***	0.97**	−0.31	−0.74	1.64***	2.6***	0.44
Physical	0.94***	1.32***	1.25***	0.79***	0.85***	1.18***	0.99***	0.85***
Social	0.40*	0.28	0.52**	0.09	−0.36	0.41**	0.9***	0.23
Financial	1.01***	0.72**	1.51***	0.84**	1.6***	0.96***	1.37***	1.58***
Constant	−3.75***	−1.06***	−4.22***	−3.48***	−5.46***	−2.92***	−5.81***	−2.79***
Random-effects parameters								
Estimate	1.47	1.19	1.64	1.21	2.53	1.58	1.39	1.17
Std. Error	0.22	0.15	0.23	0.21	0.41	0.18	0.26	0.15
Number of obs.	1538	1538	1538	1538	1538	1538	1538	1538
Number of groups	80	80	80	80	80	80	80	80
Log likelihood	−401.7	−703.8	−446.4	−340	−289.5	−719.3	−303.2	−623.78
Wald chi^2(5)	46.8***	123.1***	72.2***	18.9***	40.1***	89.8***	72.7***	69.4***
Chibar^2(01)	100.8***	120.7***	151.8***	44.3***	202***	256***	59.3***	121.42***

Source García de Jalón et al. (2017)
*$p<0.1$; **$p<0.05$; ***$p<0.01$

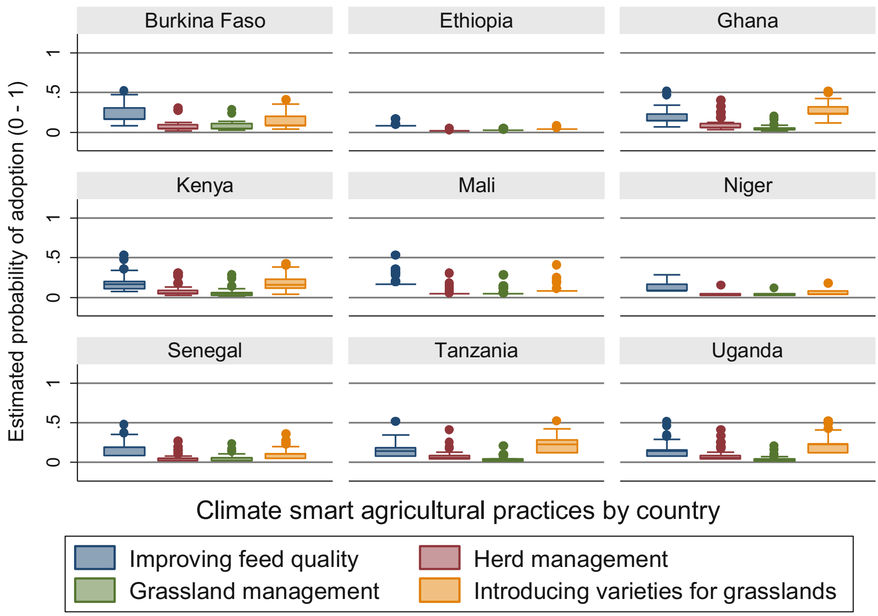

Fig. 5.5 Estimated probability of adoption of the climate smart agricultural practices for the livestock systems in the case studies of CCAFS survey. Middle horizontal lines within each box indicate the median, boxes extend from the 25th to 75th percentile and vertical lines extend from 5th to 95th percentile of estimations. *Source* García de Jalón et al. (2017)

applicability of some suggested approaches to assess the uptake of climate change adaptation strategies in Sub-Saharan Africa at different spatial scales. Whilst the case studies at the farm level were conducted with the purpose of exploring farmer behaviour towards adaptation, the case studies at the regional level attempted to up- and down-scale adoption in order to generalize theory and refine modelling estimates, respectively.

When assessing farm-level adoption and farmer choices, qualitative and quantitative data collection methods are widely used. Among qualitative methods, focus group discussions, stakeholder participatory workshops, interviews are the most commonly used. Face-to-face surveys are typically undertaken in Sub-Saharan Africa to collect quantitative data on farmer attitudes towards climate change and adoption of adaptation strategies. In order to analyze qualitative data, methods such as Participatory Rural Appraisal or Q-methodology have been used to elicit narrative statements related to farmer behaviour towards climate change. These qualitative approaches allow the exploration of farmer decision-making processes on relation to adoption of adaptation under a range of scenarios. Quantitative survey data allows the use of statistical approaches such as linear regressions to quantify the effect of the relationship among certain variables and statistical tests to contrast a determined hypothesis.

When assessing regional level adoption of adaptation strategies to climate change secondary data sources or archival data from public and private databases are commonly used from both bottom-up and top-down perspectives. The survey of the CGIAR Research program CCAFS across various Sub-Saharan African countries can also be used for assessing adoption at the regional level. Results from previous studies such as the coefficients of econometric regressions are also used to collect data in a determined region. From a bottom-up perspective, approaches that can be used to up-scale the uptake of adaptation strategies include composite indicators, deterministic farm-scale models and agent-based models. Meta-analyses reviews and syntheses can also be used to identify patterns among study results, sources of disagreement among those results, or other interesting relationships among multiple studies. From a top-down perspective, proxies of adaptation strategies and/or drivers of adoption can be used to refine modelled estimates at high spatial scales. The different types of capital can be used as proxies of drivers of adoption. The influence on these proxies can be assessed by econometric regressions.

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Part II
Macroeconomic and Complexity Modelling: Global Challenges and Multi-agent Interactions in Mitigation and Adaptation Policy Analysis

Chapter 6
CGE Models in Environmental Policy Analysis: A Review and Spanish Case Study

M. Bourne and G. Philippidis

6.1 Introduction

The publication of the Fifth Assessment Report by the Intergovernmental Panel on Climate Change (IPCC) has underlined once again the serious consequences of failing to act sufficiently to bring down global Greenhouse Gas (GHG) emissions. These consequences include (although are not restricted to) disrupted livelihoods from increased flooding; risks resulting from damage to infrastructure from extreme weather events; increased morbidity and mortality rates from periods of extreme heat and issues of food insecurity resulting from droughts, floods, and precipitation volatility. At the global level, the successor to the Kyoto agreement, the Paris Conference of Parties (COP) of the United Nations Framework Convention on Climate Change (UNFCCC) ratified in December 2015, faces new uncertainty with the United States having pulled out of the agreement. For its part, since the launch of its Emissions Trading Scheme (ETS) in 2005, the European Union (EU) has set its own relatively ambitious unilateral GHG reduction targets to 2020, with mooted GHG reductions of up to 40% (EC 2014) by 2030 (compared with 1990 levels).

The use of computable general equilibrium (CGE) simulation models in the analysis of environmental and energy policy has a long history. In seeking to provide the reader with a broad overview of the key issues currently facing CGE models in environmental policy analysis, part one of this chapter discusses the main modelling-, data- and scenario driven innovations which have occurred in the CGE literature. Thus, the chapter traces back to the early days of general equilibrium models being applied to energy and environmental issues, beginning with coverage of applications examining energy and fossil fuels, during and after the oil shocks of the 1970s. With steady improvements in computational facility and greater availability of secondary data sets, the degree of complexity of the issues tackled by CGE models

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also increased. As a result, more recent CGE studies incorporate a much more intricate representation of (inter alia) land use and production technologies, whilst other research extended the models by including bottoms up engineering estimates to anticipate potential uptake of abatement technologies in response to tighter emissions reductions. Finally, a further area of advancement has been in the modelling and scenario design to examine environmental policy options through different permit allocation schemes, issues of 'carbon leakage' or to explore the so-called 'double dividend' hypothesis.

In part two of this chapter, the focus narrows to examine an application of a single country neoclassical CGE model of the Spanish economy with a particular emphasis on the primary agricultural sectors. In 1990, Spain had the sixth highest GHG emissions of the EU27, although the ensuing period was characterised by aggressive economic growth driven by the construction boom up to the financial crisis. As a result, under a burden sharing scheme, the Spanish emissions target in 2012 was directed toward limiting the rate of increase rather than absolute reductions in Spanish GHG emissions. Nevertheless, under the Climate and Energy Package, the major sources of GHGs not covered by the ETS (waste, transport, buildings and, in particular, primary agriculture) were obliged to reduce emissions by 10% in Spain, whilst reductions in ETS sectors will be dependent on domestic allocations, and on the carbon price determined by the demand for (i.e. economic conditions) and supply of (i.e. EU policy) permits. Under three emissions reductions scenarios and employing some of the methodological innovations discussed in the literature review, a neoclassical single country CGE model of Spain examines the implications for the Spanish primary agricultural sectors and the broader macro-economy.

Part One: Key Issues in CGE Environmental Policy Modelling

6.2 Energy-Economy CGE Models

Hudson and Jorgenson (1974) constructed a model which drew on both the econometric approach developed by Goldberger and Klein (1955) and the Input-Output analysis of Leontief (1941) to project a macroeconomic growth path for the U.S. economy. This study demonstrates three principal uses of CGE in energy/environmental analysis: to project forward a 'business-as-usual' baseline, which allows analysts to explore the possible future structure of the economy in the absence of significant unforeseen changes; to analyse the impact of a given change in policy (in this case, energy taxes); and to estimate the level at which a policy (such as a tax) must be applied in order to meet a given objective (in this case, energy independence). These three uses will be seen repeatedly throughout the papers discussed below, and in this study.

The authors extended their work with an in depth analysis of the dynamic effects of energy policy on economic growth in Hudson and Jorgenson (1978), a subject also touched upon in Hazilla and Kopp (1990) and Adams et al. (2000). The common thread in all three studies is that restrictions on energy use or pollution reduce economic output in the short run, and growth in the long run, by reducing the productivity of labour and capital, as they have less energy to work with. In the short run total output is a function of the stocks of these factors and their productivity, so reducing the latter causes a contraction in the productive capacity of the economy. In the long run, lower capital returns discourage investment, and a lower real wage encourages workers to substitute leisure for labour (assuming an upward sloping labour supply curve). Thus in the long run both factor endowments and their productivities are reduced, resulting in a lower rate of growth than that which would have arisen in the absence of restrictions.

Another set of papers uses dynamic CGE models to explore the idea of 'optimal pathways' for greenhouse gas emissions over time (Nordhaus 1990, 1992; Hamdi-Cherif 2012). These inter-temporal models aim to simulate the optimal level of emissions at any given point in the simulation period. Technological progress means abatement is relatively cheaper in later periods, but an environmental damage module means there is a net present value to avoided emissions in early periods as they do not add to stocks of pollutants. Martin and Van Wijnbergen (1986) use a similar concept to map out an optimal use pathway for natural resource depletion, based on the seminal work on the subject by Hotelling (1931). This maps the rate at which a scarce resource is used up to the development of alternative technologies which do not rely on the resource and the net present values of current and expected future returns to using the dwindling resource in different periods. These studies all have to deal with the question of the discount rate, i.e. the weight which the material welfare of future generations is given relative to that of the current generation. This is a difficult issue for the economics profession as it concerns questions of ethics as well as efficiency. For example, the Stern Report on Climate Change (Stern 2007) controversially used a discount rate of zero.

A key development in the literature by Rutherford and Montgomery (1997), Böhringer (1998) and Böhringer and Rutherford (2008), was to combine the 'bottom-up' detail of an energy model with the 'top-down' interactions of a CGE model. In Rutherford and Montgomery (1997), the CGE model derives energy demands which are an input into the partial equilibrium (PE) model used to derive energy prices, which then feedback into the CGE model—an iterative process which repeats itself until the results of the two models converge. Böhringer (1998) and Böhringer and Rutherford (2008) employ model complementarities within the energy sector such that specific types of plants come online when they become profitable, and a non-zero price for a specific energy source emerges when demand reaches supply, with plant costs and capacities coming from bottom-up energy data.

A further development for characterising energy sectors in a CGE model was through the representation of their production technologies. More specifically, the 'nesting' structures within the production function are arranged, subject to the availability of plausible substitution elasticities, to determine more accurately the production processes which govern output in these industries. An early example is the OECD's GREEN model (Burniaux et al. 1992; Lee et al. 1994), wherein the top nest of energy inputs, firms choose between an electricity composite and non-electrical energy. At the next level down the non-electrical composite divides into coal on one branch, and an oil and gas composite on the other, and at a further level down the oil and gas composite splits into those two fuels. This general approach has filtered into the mainstream literature through its adoption in (inter alia) the GTAP-E model (Burniaux and Truong 2002), the MMRF-Green model (Adams et al. 2000), and the ORANI model (Horridge et al. 1993).

6.3 Different Pollutants and Environment-Economy Feedbacks

In the environmental extension to his Input-Output framework, Leontief (1970) illustrated the importance of how pollution is assigned by taking the data for emissions by industry, and reallocating it on the basis of emissions embodied in final demands. In presenting, if only briefly, this form of analysis, Leontief showed an early form of the so-called 'farm to fork' method of measuring total emissions associated with the production of a given agricultural commodity, which has more recently garnered increasingly popular in academic and policy circles (FAO 2010). In the same study he extended the notion of 'input-output coefficients' to 'discharge coefficients' which attach pollution to output or to the use of certain inputs in specific industries. A similar approach was adopted by Willett (1985), Conrad and Schröder (1991) and numerous studies since.

In the DICE global climate change model, and its regional counterpart RICE, Nordhaus (1990) and Nordhaus and Yang (1996) include an environmental damage function which translates stocks of greenhouse gases in the atmosphere (which grow each year with emissions) into radiative forcing which provokes a global temperature increase causing economic damage, the severity of which varies between industries. In the latter study, the regional component of the damage function comes from the fact that different industries have different weightings in different regions, not because of any geographical features of the regions in question. By contrast, the GEM-E3 model (Capros et al. 2013) tracks the stocks of a number of different pollutants, and translates them into specific geographical areas and damage functions. Concentration of pollutants causes damages to human health, soils, forests, buildings and territorial eco-systems. Other studies which include feedback mechanisms from the environment to the economy include Vennemo (1997) and Xie and Saltzman (2000). Both include a negative relationship between increasing pollution and factor productivity, and a direct effect of pollution on utility.

6.4 Land Use Change and Forestry

Ahammad and Mi (2005) adapt the Global Trade and Environmental Model (GTEM) to include eighteen different land types based on Agro-Ecological Zones (AEZs). The AEZs distinguish land on the basis of three different climate areas (tropical, temperate and boreal), and 6 different lengths of growing season. The supply of each type of land is fixed, but the production function for agriculture is modified to allow farmers to substitute between the different land types, and between land and fertiliser at a low level of the nest. In addition, the stock of forest area is disaggregated by age, land class and management type, with different carbon densities associated with each. A Constant Elasticity of Transformation (CET) function determines at the first level the movement of land between agriculture and forestry, and then at higher levels the movement of land between different agricultural uses. While most GHG emissions from agriculture are attached to fertiliser use or livestock output, emissions of N_2O from soil disturbance are dependent on the area of land used for agriculture. Net emissions from forestry depend on the change in the carbon stock of forest land, which is a function of the area de- or re-forested, its timber yield, and associated carbon stocking density. Policies to regulate or tax emissions are thus likely to encourage forestry at the expense of agriculture by effectively subsidising land used in forestry and taxing the agricultural sector.

This approach is also used in Golub et al. (2009) with some variations. The paper contains a detailed treatment of the rate at which previously inaccessible forests are accessed depending on the land rents available and the cost of accessing land. The former increases with demand for crop, livestock and forestry products leading to a derived demand for increased land, while the latter increases with the proportion of total land which has been accessed, reflecting the fact that as more land is demanded, the land coming into production is more marginal and so costs more to access. This leads to a Ricardian treatment of land rents whereby inaccessible land will be brought into production when the net present value of the land is equal to the cost of accessing it, so as accessed land increases, rents will rise on previously accessed land. Golub et al. (2009) also explicitly distinguish between the intensive and extensive margins for carbon sequestration in forestry. The extensive margin governs the decision to cut down or plant forests, and is dependent on the land rents and demand. The intensive margin is the potential for a fixed area of forest to hold more carbon through the ageing process, or changes in management practices. This is modelled by increasing the use of forestry products in the forestry sector, thus decreasing net output in order to increase the timber—(and hence carbon) intensity of forests.

Bosello et al. (2010) use a CGE model to analyse the importance of the scheme Reducing Emissions from Deforestation or forest Degradation (REDD) in EU emissions reduction targets for 2020. In their model, the avoidance of deforestation in Latin America, Sub-Saharan Africa and South East Asia generates carbon permits which can be sold on the EU ETS market. This results in a transfer of payments from the EU to those regions, but also reduces land available for agriculture, and timber available for wood products. They find that the inclusion of REDD credits significantly reduces the ETS permit price, but also leads to an increase in the price of land, which is strongest in South East Asia, and the price of timber, particularly in Sub-Saharan Africa.

A number of studies use CGE models to investigate the effects of the re-cent growth in biofuels production on land use and on emissions reduction possibilities. One such paper is Birur et al. (2008), which modifies a version of the GTAP-E model to include biofuels used by both consumers and producers, and land use type by AEZ. The paper distinguishes between cereal- and sugar-based bioethanol and biodiesel from vegetable oil. This distinction is significant as each has different 'feedstock' crops, so each will have different impacts on land use change, as well as having more natural advantages in different geographic areas. Consumers in the model treat each type of biofuel as highly substitutable with petrol, whilst in production, biofuel is treated as a Leontief complement to petrol use. On the supply side, a CET function governs the ease with which land of each AEZ can move between different uses, with a much higher elasticity between different crop types than crops and pasture, or at the most extreme agriculture and forestry. It is this which restricts land use changes, as farmers are seen as relatively indifferent as to which type of land they use, with a high elasticity of substitution between different AEZs in the agricultural production function.

6.5 Marginal Abatement Cost (MAC) Curves in CGE Models

A number of the papers already mentioned above include some approximation of end-of-pipe abatement options. Xie and Saltzman (2000), for example develop an Environmental Social Accounting Matrix (ESAM) for China based on the extended input-output table in Leontief (1970). The ESAM includes intermediate and factor purchases for abatement by each industry in the model, as well as government purchases of pollution cleaning services. Bergman (1991), Conrad and Schröder (1991), Adams et al. (2000) and the GRACE model (Rypdal et al. 2007; Rive 2010) all allow firms to use additional quantities of factor and inter-mediate inputs to reduce pollution, although in none of these papers is such 'cleaning' the focus of the study.

An important early study on the inclusion of what has come to be known as 'end-of-pipe' abatement in CGE models was that by Nestor and Pasurka (1995a, b), who used detailed German data showing expenditure on specific abatement inputs to extend the input-output data to include both those which are internal to the firm (i.e. use the firm's own labour and capital), and intermediate inputs purchased from an abatement sector. They note that CGE models offer a significant advantage in modelling environmental compliance as the costs of pollution reduction may be mitigated for those industries whose output is used in abatement activities. As an example, their results suggest that the (German) abatement sector is relatively energy intensive, such that the direct effects of environmental policy on the energy sectors are reduced by the increase in energy demand from the rest of the economy as abatement increases. In this study a government agency collects all abatement expenditure as a ‘tax’ and uses it to hire factors and buy inputs from the abatement sector. In recent years, a number of researchers have treated emissions as a necessary input into production. One of the first studies to use this approach as a step towards incorporating MAC curves into a CGE model was Hyman et al. (2003), which treats emissions as an additional input within the production process by characterising CES possibilities between greenhouse gas emissions and the use of a composite input (i.e., intermediate inputs and primary factors). Thus firms can reduce their emissions either by reducing their output, or by increasing their use of all conventional inputs relative to output. The elasticity of substitution between emissions and the conventional inputs composite is then calibrated for each industry to match its MAC curve. The most important implication of this approach, in the light of the current study, is that it implicitly assumes that abatement expenditures will have the same cost structure as the industry’s production process. This is a significantly different approach to Nestor and Pasurka (1995a, b), described above. Essentially, comparing across different industries, the cost shares of abatement expenditure following the Nestor and Pasurka approach will be the same, whereas in the Hyman et al. (2003) approach, they are approximated by the production cost shares in each industry.

A number of papers (Dellink 2000; Dellink et al. 2004; Dellink and Van Ierland 2006; Gerlagh et al. 2002) use detailed data on abatement options and their associated costs in the Netherlands to construct a single MAC curve for each environmental ‘theme’, such as climate change or acid rain. Thus all available technologies for the abatement of any greenhouse gas in any industry are included in the same MAC curve, which avoids the problem of a small number of data points in calibration. Similar to Hyman et al. (2003), pollution is treated as a necessary input into production, and an elasticity of substitution is calibrated to the MAC curve. However, in this case, the elasticity is not at the top level of the nest, but rather between abatement and abatable emissions. These papers also include a maximum technical abatement potential (based on the data on abatement technologies) such that a certain proportion of emissions is classified as ‘unabatable’. These are produced in fixed proportions to output, as is the composite of abatable emissions and abatement measures. Akin to the Nestor and Pasurka approach, a single abatement sector provides ‘abatement measures’ to every industry for each environmental theme. In some respects this approach could thus be seen as an attempt to reconcile the two methods described above.

The current state of the art in this field is described in Kiuila and Rutherford (2013). The paper compares, on the one hand, sector specific and economy-wide approaches to abatement and, on the other hand, ‘traditional’ and ‘hybrid’ approaches. Briefly, the sector specific approach treats abatement as internal to each industry in the model. This can be seen as the optimal method, but can be limited by data availability. The economy-wide approach has an ‘abatement sector’, from which all other industries purchase abatement services, which assumes the cost structure of abatement technologies is constant across abating industries and gases. Furthermore, the traditional approach has a smooth (CES) production function for abatement, whilst the hybrid approach attempts to integrate stepwise MAC curves from bottom-up data though Leontief functions for specific technologies that become active when the carbon price reaches a certain 'trigger' level. The study suggests that at low levels of abatement, a smooth approximation gives similar results to the stepwise function. When abatement options reach their maximum potential though, the step function approaches infinity more immediately than the smooth curve, so at these higher levels of abatement the traditional approach may overestimate abatement potential.

6.6 Emissions Reduction Options

Many of the early studies of environmental policy focussed on standards and restrictions on emissions (see, for example, Blitzer et al. 1994; Ellerman and Decaux 1998; Wang et al. 2009). The results tend to support (or are caused by) the neoclassical assumption that the cheapest options for reducing emissions (the so-called 'low hanging fruit') will be exploited first, thus the marginal cost of abatement rises with abatement. This result is found so consistently that it seems generally sound, but a note of caution is needed. Some abatement technologies (specific types of renewable energy, or carbon capture and storage, for example), may require high levels of initial investment to reach a 'tipping point', after which the marginal costs of spreading the technology (and the resulting abatement) may be significantly lower. If enough abatement technologies follow this pattern, the effect may be enough to cause a kink in the otherwise smoothly convex cost curve for emissions reductions. These complexities often relate to industry structure, and are difficult to include in a CGE context, but modellers should be aware that they are implicitly assuming perfect knowledge of the total (investment and operating) costs of emissions reduction options, and of their abatement potential.

A number of global CGE models have shown the importance of including non-CO_2 gases by comparing on the one hand, scenarios where temperature or radiative forcing (see footnote 3 above) targets are met solely through reductions in CO_2 emissions with, on the other hand, studies where other GHGs could contribute to meeting the target (Hyman et al. 2003; Bernard et al. 2006; Tol 2006). A significant and consistent finding across the papers was that non-CO_2 gases are likely to contribute a relatively higher proportion of emissions reductions when the total target is less stringent. This is because abatement options for these gases tend to be cheaper than those for CO_2, but technically limited. Thus as emissions reduction targets become more stringent, CO_2 takes more of the burden—though obviously with some variation between regions. All the studies found that a consideration of non CO_2 gases can significantly reduce the cost of meeting overall targets, and this approach has become the normal method in the years since.

Bergman (1991) and Rutherford (1992) were among the first studies to attach permits to fossil fuel combustion emissions and force an endogenous permit price to emerge by exogenously restricting the supply of permits. Bergman (1991) reports that if pollutants are concentrated in a few sectors of the economy, the remaining sectors may actually benefit from pollution controls, as factors of production are released from the constricting sectors, bringing their price down. In contrast, Hazilla and Kopp (1990) note that introducing environmental regulations to only a few industries causes prices to rise, and production to fall, in every sector of the economy, as the regulated sectors are used as intermediate inputs in other industries.

As stated in the introduction to this chapter, a strength of CGE models is that they can simulate multiple policies simultaneously and be used to explore how these different policies interact (and possibly conflict) with each other. Morris (2009) uses a CGE model of the U.S. to examine the effects of a cap-and-trade scheme and a 'Renewable Portfolio Standard' (RPS), which mandates that a minimum percentage of electricity come from renewable sources. Each policy is first modelled in isolation, and then both at the same time to see how each affects the other. Interestingly, the results suggest that in the presence of a cap-and-trade scheme to achieve a given emissions reduction, adding the RPS causes an additional welfare loss with no extra GHG mitigation. By adding the RPS on top of the cap-and-trade policy, one is essentially mandating how a certain portion of the emissions reduction target is to be met (i.e. through carbon-free electricity) as op-posed to allowing all abatement to occur where the marginal cost is lowest. Of course, if switching to renewable electricity was the cheapest way of meeting the emissions target, the RPS would be non-binding and adding it into the policy mix would have no effect on either welfare or the carbon price.

Another issue of interest is how industry- or country-specific targets (as opposed to permit trading schemes) affect industries or countries with low benchmark emissions intensities. Blitzer et al. (1994), for example, find that in the sector-specific case, stringent reductions are infeasible in the services sector due to a lack of substitution possibilities—forcing them to exempt services from reductions in those scenarios. In a similar vein, Paltsev et al. (2004) find that the high level of energy efficiency in Japan means that there are few cheap abatement options available as further efficiency improvements are likely to be expensive. This translates into the highest direct abatement costs of all Annex I regions in terms of $/t$CO_2$ abated. This does not, however, translate into the highest welfare cost as the small size of the energy sector relative to total output means that energy cost increases do not have such a significant effect on the rest of the economy as they do in other Annex I countries, where the energy sector is larger. Hence in the current study there may be some industries with low emissions intensities which need an extremely high carbon tax in order to meet an industry-specific reduction target, though this high tax may not translate into large price increases due to the same low emissions intensity that caused it.

Two further studies (Bye and Nyborg 1999; Edwards and Hutton 2001) merit a mention for their research on optimal permit allocation mechanisms. More specifically, these studies examine permit auctions and 'grandfathering' (i.e., distributed for free on the basis of historical emissions). Both studies find that grandfathering permits acts as a significant barrier to entry to the industries in the permit scheme, as well as provoking windfall profits and a transfer of money from the public to the private sector. This is particularly true in Bye and Nyborg (1999) where the permit scheme replaces existing energy taxes but must be revenue neutral, so payroll taxes must increase to offset the lost tax revenues. The paper's principal contribution is the observation that in the design of policies for environmental taxation (and/or permit schemes), there are two kinds of efficiency that need to be borne in mind. One may be termed 'environmental efficiency' and consists in ensuring that pollution abatement happens where the cost of such abatement is lowest. The other ('tax efficiency' perhaps) concerns the effects of the tax on the general economy. The suggestion is that certain fuels are taxed more heavily than others due to low elasticities of demand. Reducing the tax rates on such fuels thus causes a significant loss in revenue which, ceteris paribus, must be raised by tax increases elsewhere. Of course, the premise that taxes on more inelastic goods are less distorting is moot, and will be discussed further in the analysis of the results presented here—specifically in relation to the effects of emissions policy on globally competitive Spanish export sectors, and the extent to which they should be protected from policy-induced price rises. Finally, Edwards and Hutton (2001) report that when permits are auctioned, and the revenues are recycled as an output subsidy, there may be a 'double dividend', i.e. emissions reductions may be achieved in conjunction with some other policy goal, usually economic growth or increased employment. It is to such possibilities for revenue recycling that we now turn.

6.7 Trade and Carbon Leakage

Devarajan (1989) notes how energy-economy models were used, amongst other things, to look at the phenomenon of oil price rises for exporting countries, including the so-called 'Dutch Disease' problem whereby rising revenues from a natural resource export causes a real appreciation of the currency which is damaging for other export-oriented, or import-competing, industries. Benjamin et al. (1989) construct a CGE model which suggests that this is in fact the case for the export sectors, but that the degree to which import-competing sectors suffer de-pends on the degree of substitutability between the domestically produced goods and imports—a parameter which often carries a degree of uncertainty in economic models.

Burniaux et al. (1992) uses the OECD-GREEN model described above to examine how distortions in global energy markets affect policies to reduce CO_2 emissions. These distortions generally take the form of taxes in OECD countries, and subsidies in non-OECD countries, and this has a significant bearing on the results. They find that eliminating all energy market distortions (i.e., subsidies and taxes) globally is sufficient to reduce CO_2 emissions by 18% on the baseline in 2050, and the falling world oil price resulting from reduced demand means even the non-OECD countries (with the exception of energy exporters) witness a welfare improvement from such a liberalisation scenario. This paper highlights the importance of 'joined up thinking' in energy policies, and outlines the potential for the removal of existing energy subsidies to make a significant—if not entirely sufficient—difference to GHG emissions. Indeed, taking a medium-term scenario to 2030, Maisonnave et al. (2012)

explore the impact of (unilateral) EU climate policy on the import cost of oil prices to the EU, as well as the effect that steep in-creases in the oil price have on the costs of EU climate policy. They find that climate policy reduces the cost of the oil price by approximately a third or, alternatively, that a high oil price could reduce the cost of climate policy dramatically—by more than two thirds.

Gerlagh et al. (2002) and Blitzer et al. (1994) both find that when emissions restrictions are applied unilaterally in a single country model, the comparative advantage of the country in question shifts towards less polluting products, and more emissions intensive products are increasingly imported from abroad—otherwise known as 'carbon leakage'. The picture is the most stark in Blitzer et al. (1994), with results suggesting that while oil would still be mined in Egypt in the presence of emissions restrictions, it would be exported to be refined, with the petroleum products then reimported.

Babiker et al. (1997) investigate two options for addressing carbon leakage when emissions restrictions are only applied to OECD countries: Border Tax Adjustments (BTAs) depending on the carbon content of imports, or restricting exports from countries not limiting their emissions. The first seems the most logical approach, and indeed it reduces carbon leakage to zero, and reduces the necessary permit price by around 10%. In welfare terms the losses to the OECD countries from the carbon tax are mitigated, but the result is that the non-OECD countries suffer a welfare loss. Alternatively, non-OECD countries fare better under the export restriction scenarios, although this does not reduce the permit price, or carbon leakage rates by as much. This study reinforces the importance of the carbon leakage issue, as well as the need (and opportunity) to set emissions policy simulations in the context of other policies relevant to the period being studied—trade or agricultural policies for example.

Bosello et al. (2013) also study two options for mitigating carbon leakage, this time from the EU: Border Tax Adjustments (BTAs) on imports to tax them according to carbon content, and the assumption that non-EU countries will also face emissions restrictions. BTAs reduce GDP as the improved competitive-ness of domestic production is balanced by increased costs for firms which import intermediate inputs—dependent on the degree to which imports are substitutes or complements to domestic production. Similarly, the imposition of emissions reduction policies in non-EU regions does not have an unambiguously positive effect in the EU, as the substitution effects towards EU exports is balanced by an income effect as global GDP growth is slowed, reducing trade volumes overall.

Part II Spanish Case Study: Spanish Agricultural Emissions

This case study uses a single country neoclassical CGE model to analyse the effects of agreed emissions reductions on the agricultural sector over the period 2007–2020. The model employs Spanish input-output data for the year 2007. With a starting point in 2007, the study is carefully baselined to 2020 employing a mix of historical observations on the components of aggregate demand and population, and projections data for growth and population in Spain. Where possible, both technological change and taste shifters have been employed to capture as reasonably as possible the trends in the Spanish economy up to the latest available period. To understand the different emissions intensities within different agricultural activities, a detailed agricultural sector split of the parent activity of ‘agriculture, forestry and fishing’ in the national accounts, is required. In addition, to improve the validity of the research, both agricultural factor market and product market (i.e., the Common Agricultural policy) rigidities are modelled explicitly for Spain. Associated emissions data for the Spanish economy is taken from the UNFCCC, which disaggregates emissions of six GHGs (CO_2, CH_4, N_2O, HFCs, PFCs, HS6) into the following categories. In the model these emissions are mapped to the classification of sectors in the model, whilst drivers for each emitting activity (i.e., combustion and non-combustion) are assigned. European Union environmental policy is characterised explicitly through the modelling of the ETS scheme, where an exogenous (projected) permit price is assumed, whilst diffuse sectors (i.e., non ETS sectors) classified as transport, waste and buildings and agriculture, face emissions reductions subject to a carbon tax. All emissions target reductions are set as lower limits, such that a non-binding emissions target results in a zero permit price/carbon tax. A key innovation in this study is the implementation of available ‘end-of-pipe’ reductions discussed in Sect. 6.5 in part 1 of this chapter, through investment in abatement technologies such as precision farming or anaerobic digestion. The MAC curves are discussed further in Sect. 6.9.

6.8 Agricultural Emissions in Spain

In 2007, Spanish agriculture was responsible for 53 million metric tonnes (Mmt) of Carbon Dioxide Equivalent (CO_{2e})—around 12% of Spain’s total of 444 Mmt. Food production adds another 3.75 Mmt—less than 1% of the Spanish total. Agricultural emissions are dominated by methane (CH_4) and nitrous oxide (N_2O). Indeed, when Spanish emissions of non-CO_2 GHG emissions only are considered, the proportion corresponding to agriculture rises dramatically to 59%.

The breakdown of agricultural emissions can be seen in Fig. 6.1. Cattle (including dairy cattle) and sheep contribute over a third of the agricultural total, while the combined livestock emissions are over half the total. Among the crops sectors, emissions from cereals production are significant, but olive growing is the single industry with the largest emissions, with over 10% of the agricultural total.

Another measure of how polluting an industry is the ‘emissions intensity’—the quantity of GHGs emitted per euro of industry output. These figures are presented in Table 6.1, which shows fruit and vegetable growing to be the least emissions intensive agricultural activities, emitting 0.59 and 0.14 kgCO_{2e}/€ respectively, compared to 1.72 for cereals, and 3.78 for olives. It should be noted that the fruit aggregate masks some significant differences, as it includes grapes (1.88 kgCO_{2e}/€) and citrus (0.27 kgCO_{2e}/€). The table suggests cattle and sheep farming are more emissions intensive than pig and poultry farming, but less so than olive growing. These emissions intensities become relevant when examining the results of the scenarios. For example, while fruit and vegetable growers may find it more difficult to reduce the relatively small amount of (predominantly combustion) emissions they do produce,

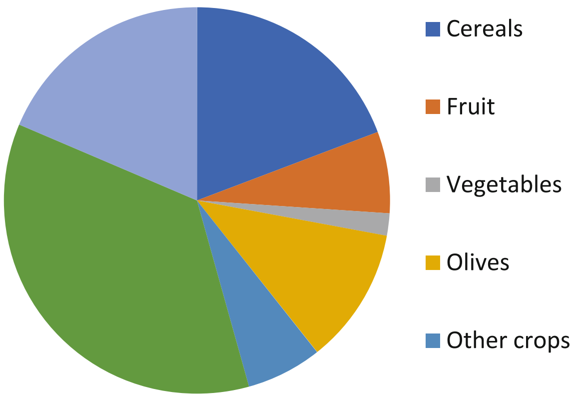


Fig. 6.1 Breakdown of agricultural emissions in 2007

Table 6.1 Emissions intensities of various agricultural activities in 2007

Industry	Emissions ($MmtCO_{2e}$)	Size (€ millions)	$kgCO_{2e}$/€
Cereals	10.24	5966	1.72
Fruit	4.62	6139	0.59
Vegetables	0.99	7039	0.14
Olives	6.07	1606	3.78
Cattle and sheep	19.03	7824	2.43
Pigs, poultry and other animals	9.89	8729	1.13
Agriculture	53.22	42,644	1.25
Spanish industrial total	358.53	2,071,404	0.17

by the same token, the increase in total costs from any tax on emissions will impact less in this sector (in proportional terms) than in an industry with a high emissions intensity (i.e., olives). This brings us to the next section, which discusses the sources of agricultural activity emissions and the degree to which they can be abated.

6.9 Emissions Factors and Marginal Abatement Cost (MAC) Curves

As well as the quantity of emissions associated with each agricultural industry, it is useful to be aware of where those emissions come from, as this has implications for their abatement possibilities. Emissions which come from petrol combustion, for example, are difficult to mitigate as petrol is the only non-electric source of energy used in significant quantities by farmers, so substitution possibilities are limited. The proportion of combustion emissions is very small in the livestock sectors—around 0–6% (not shown). In the crops sectors emissions factors are considerably higher.

Olives have the lowest proportion, at around 13%, whilst for the cereals and fruit and vegetables sector, about one-third of emissions come from fuel combustion, and in the remainder of the crops sectors the average is almost one-half. These emissions cannot be reduced by ‘end-of-pipe’ abatement measures.

Further evidence suggests that N_2O from manure is impossible to abate. If these N_2O emissions are added to those from fuel combustion, it brings the proportion of livestock sector emissions which are impossible to abate up to around 21%, much closer to the average for crops. For the remainder, the ease of abatement is governed by the MAC curves (Figs. 6.2 and 6.3) which show the ease of the uptake of abatement technologies (governed by the slope) at different carbon prices.

The first thing to notice from these graphs is how much cheaper abatement is in livestock than crops at any point up to the technically feasible maximum (around 25%). Considering the emissions reduction target of 10%, this means end-of-pipe abatement is likely to be heavily concentrated in livestock sectors. Thus, Fig. 6.3 reveals that 20% of livestock methane emissions could be abated for less than €10/tCO_{2e}. This translates to 4.6 MmtCO_{2e}, or 8.6% of total agricultural emissions in the benchmark. If this were the case, the crops sectors would have to contribute relatively little abatement in a scenario where the 10% reduction is an aggregate target applied to the agricultural total. If each agricultural industry must individually meet the 10% target, it implies that the target is likely to be easily met in the livestock sectors, meaning some relatively low-cost abatement opportunities may not be taken up, whilst the crops sectors are forced to engage in relatively expensive abatement options. The expectation is that this will increase the overall cost of an industry-specific target relative to a single one for the agricultural sector.

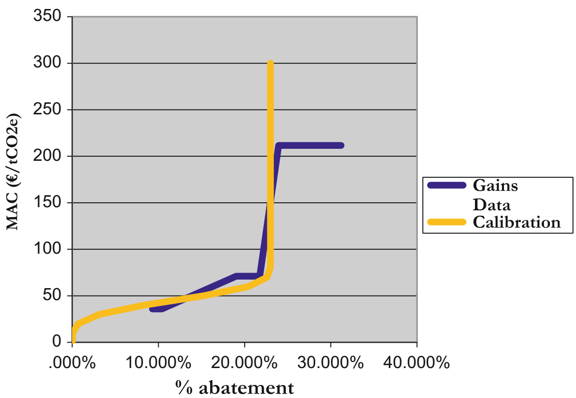
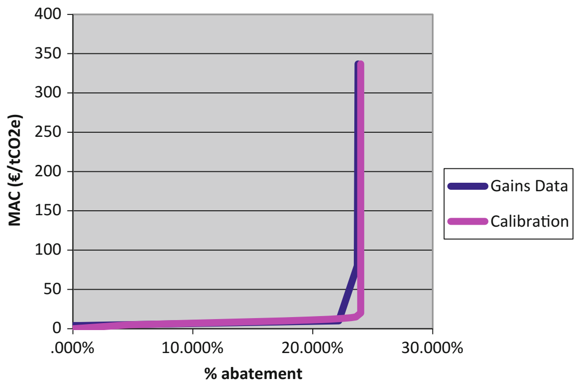


Fig. 6.2 Calibrated MAC curves for N_2O emissions from fertiliser use

Fig. 6.3 Calibrated MAC curves for CH_4 emissions from livestock



6.10 Scenarios

The baseline, or status quo reference scenario, contains neither restrictions on Greenhouse Gas (GHG) emissions nor any kind of emissions tax. Whilst this is clearly unrealistic, the purpose is to give a counterfactual in order to isolate the effects of environmental policy in the results from all following scenarios. The policy shocks which are employed to characterise the CAP remain unchanged in the baseline and all scenarios, in order to fully isolate the effects of emissions restrictions in agriculture.

The key features of each scenario are shown in Table 6.2. Scenario 1 does not include the calibrated MAC curves for end-of-pipe abatement of agricultural emissions, in order that the effect of these can be isolated in scenario 2. All other features are constant across these two scenarios, with a 10% reduction in aggregate agricultural emissions, and the emergence of a single agricultural emissions price. This could be likened to an emissions trading scheme applied to agricultural emissions in isolation from any other emissions targets or permit trading schemes. Alternatively, it could be seen as a hypothetical exercise in finding the 'optimal' distribution of reductions across agricultural industries, with and without end-of-pipe abatement. Those industries with a cost of abatement higher than the agricultural average will reduce emissions by less than 10%, with the slack taken up by industries with cheaper abatement options. Scenario 3 precludes this possibility by requiring each one of ten agricultural subgroups (Table 6.3) to meet the 10% target. As a result, ten different agricultural emissions prices emerge, although in some cases the 10% reduction may be non-binding, resulting in an emissions price of zero.

Table 6.2 Scenario descriptions

Scenario	ETS emissions	Non-agric diffuse emissions	Agricultural emissions	End-of-pipe abatement in agriculture?
Baseline	Zero ETS price	Unrestricted	Unrestricted	No
Scenario 1	Exogenous non-zero ETS price	Reduced by 10% for each industry	Aggregate emissions reduced by 10%—single carbon price	No
Scenario 2	Exogenous non-zero ETS price	Reduced by 10% for each industry	Aggregate emissions reduced by 10%—single carbon price	Yes
Scenario 3	Exogenous non-zero ETS price	Reduced by 10% for each industry	Emissions of each specific agric industry reduced by 10%—multiple carbon prices	Yes

Table 6.3 Emissions factors 2007–2020 (%)

Industry	Scenario 2 relative to baseline/scenario 1	Scenario 3 relative to baseline/scenario 1
Cereals	−2.6	−5.4
Fruit	−2.6	−21.9
Vegetables	−2.6	−22
Olives	−2.6	−19.5
Other crops	−2.6	−15.8
Cattle and sheep	−21.7	0.0
Raw milk	−23.5	−28.1
Pigs	−21.6	−11.4
Poultry	−22.1	−7.1

6.11 The Distribution of Emissions Reductions

6.11.1 Scenario 1: 10% Reduction in Aggregate Agricultural Emissions, no End of Pipe Abatement

Having discussed the baseline results above, the first thing to notice is that in scenario 1, emissions reductions are concentrated in the cereals and cattle and sheep sectors, with other crops being the only other industry to contribute more than the 10% average across agriculture (Fig. 6.4). A general pattern in moving from the baseline to scenario 1, however, is that the change in emissions between the two scenarios tends to be greater in the crops than in the livestock sectors, with overall fertiliser emissions

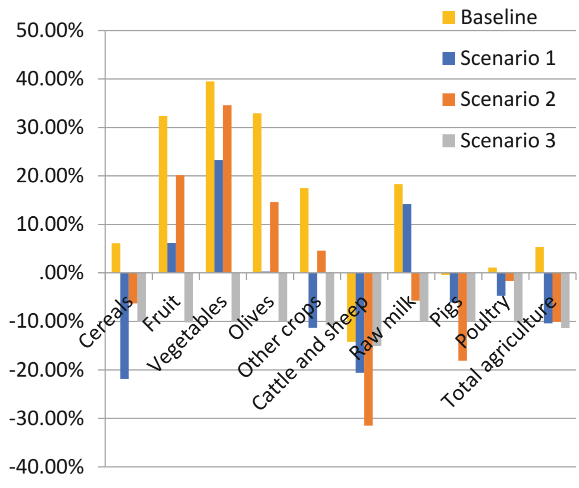


Fig. 6.4 Cumulative changes in emissions 2007–2020, baseline and scenarios 1–3

from the crops sectors 23.5% lower than the baseline in scenario 1 (not shown), and enteric fermentation and manure management emissions from livestock just 5.6% lower. This is because in the absence of end-of-pipe abatement options, the only two ways for emissions to fall are by substituting away toward less polluting inputs and/or a contraction in output. In the model, non-CO_2 emissions from livestock activities are attached to output, so the substitution option is only available to the crops sectors, which have some flexibility to reduce their fertiliser use if they increase their use of other inputs such as land, labour or capital. This extra abatement option explains why the introduction of an emissions tax provokes a bigger emissions reduction in the crops than the live-stock sectors. Taken in isolation, the effect of this substitution would be to increase the pressure on primary factors. However, the substitution effect towards factor use in the crops sectors takes place in the context of agricultural (and other) industries contracting relative to the baseline, so the 'income' effect is to lower factor prices.

6.11.2 Scenario 2: 10% Reduction in Aggregate Agricultural Emissions, with End of Pipe Abatement

The only difference between scenarios 1 and 2 is the inclusion of end-of-pipe abatement options from the calibrated MAC curves, and the effect is to concentrate emissions reductions in the livestock sectors, allowing the crops sectors to increase their emissions relative to scenario 1 such that the overall 10% reduction target for aggregate agricultural emissions is still met. At low levels of abatement, there are cheaper options available in livestock emissions (largely feed changes) than in the crops sectors. Thus, the relatively low emissions price necessary to meet the prescribed target provokes more abatement in the former than the latter. This can be seen in Table 6.3 which shows how emissions factors change in the different scenarios. The first column of Table 6.3 shows how significant the end-of-pipe abatement is in the livestock sectors in scenario 2, with emissions factors around 22% lower in 2020 than they are in the baseline/scenario 1. In contrast, those for the crops sectors fall much less, and are just 2.6% lower than the base-line/scenario 1 in 2020. This explains the result that the inclusion of end-of-pipe abatement places greater emissions reductions in the livestock sectors in the presence of a single 10% target for aggregate agricultural emissions.

6.11.3 Scenario 3: 10% Emissions Reduction in Each Agricultural Sector, with End of Pipe Abatement

The difference between scenarios 2 and 3 is that in the former, emissions reductions can vary between agricultural sectors as long as the overall 10% target is met by the agricultural sector. In scenario 3, however, each individual agricultural activity is forced to meet the 10% target itself. As can be seen in Fig. 6.4 this results in an overall reduction of slightly more than 10%, as for cattle and sheep emissions the target is non-binding, and emissions fall by 14%, whilst all other agricultural emissions fall by 10%. The movement from scenario 2 to 3 is thus beneficial for those industries which were overshooting the 10% target in scenario 2 (cattle and sheep, and pigs), whilst those industries with the highest emissions in scenario 2 (vegetables, fruit and olives) will find the enforced 10% target in scenario 3 the most stringent. To see this reflected in the results, attention now turns to the emissions taxes which emerge in each scenario.

6.12 Emissions Taxes

In the baseline emissions are unrestricted, so the endogenous emissions tax re-mains at zero. In scenarios 1 and 2, the single target for a reduction in aggregate agricultural emissions results in a uniform tax rate per tonne of CO_2 equivalent (€/tCO_{2e}) across all agricultural emissions. In both scenarios this tax rises as the period progresses and the emissions restriction tightens. By 2020 the necessary tax has reached €85/tCO_{2e} in scenario 1, but this is greatly reduced by the addition of end-of-pipe abatement, to €23/tCO_{2e}. It should be noted that this does not mean that meeting the target is 85/23 times cheaper for farmers in scenario 2, since in the modelling, agricultural activities must also meet the investment cost of in-vestment in abatement equipment, which is absent in scenario 1. Nevertheless, the presence of end-of-pipe abatement

Table 6.4 Emissions changes from scenario 2 and taxes from scenario 3

Industry	Scenario 2 cumulative emissions change (%)	Scenario 3 emissions tax in 2020 (€/tCO_{2e})
Cereals	−6.3	30.9
Fruit	20.2	91.2
Vegetables	34.6	259.3
Olives	14.6	63.6
Other crops	4.6	52.4
Cattle and sheep	−31.5	0.0
Raw milk	−5.7	11.1
Pigs	−18.1	7.8
Poultry	−1.7	412.3

options does mean that the emissions tax necessary to bring emissions down to the policy-mandated levels is much lower, as a given tax now provokes a much higher degree of abatement.

Scenario 3 is unique in that each subgroup of agricultural industries faces a specific emissions tax necessary to force each of them to reduce their emissions by 10%. In general it is to be expected that those industries with the highest emissions in scenario 2 will face the highest emissions taxes in scenario 3, as they are the ones for which abatement is most costly, given the baseline economic conditions and the MAC curve data. As shown in Table 6.4, vegetable growing has the largest emissions increase in scenario 2, and the second highest emissions tax in scenario 3, whilst the greatest emissions reduction in scenario 2 is in cattle and sheep, and this is the only industry to face a zero emissions price in scenario 3. In general, the livestock sectors tend to have lower emissions taxes in scenario 3, the exception being poultry farming. The total emissions from the poultry sector are small, but they also include a relatively high proportion of energy emissions, meaning the MAC curves for livestock are barely applicable. As has been noted above, energy emissions are hard to abate, and thus the high emissions tax necessary to force poultry emissions down 10%.

The total direct costs of each scenario to different agricultural groups are shown in Table 6.5. These are calculated as the sum of environmental taxes and abatement expenditure, accumulated over the 13 year simulation period. The results show that the introduction of end-of-pipe abatement dramatically reduces the cost to the agricultural sector as a whole from over €14 billion in scenario 1 (just over €1 billion/year) to just under €4 billion in scenario 2 (approximately €300 million/year)—a fall of around 70%. The activity-specific targets in scenario 3 raise the total cost back up to €6.2 billion, suggesting there are macroeconomic gains to be made from having a single uniform emissions price—a cap-and-trade scheme, as laid out in Weitzman (1974). Only the non-poultry livestock sectors benefit from the activity specific targets for the reasons discussed above. To fill out this emerging picture, the focus now turns to the effects each scenario has on agricultural prices and production.

Table 6.5 Total direct cost of each scenario

€ millions	Scenario 1	Scenario 2	Scenario 3
Cereals	2464	762	1060
Fruit	1057	311	956
Vegetables	323	91	608
Olives	1743	520	1706
Other crops	896	273	684
Cattle and sheep	3827	1021	0
Raw milk	1052	270	230
Pigs	2427	642	358
Poultry	153	42	594
Agriculture	14,064	3964	6246

6.13 Market Impacts

6.13.1 Scenario 1: 10% Reduction in Aggregate Agricultural Emissions, no End of Pipe Abatement

The broad picture from scenario 1 is that in the absence of end-of-pipe abatement measures the price effects of emissions restrictions are heaviest in the most emissions intensive sectors (olives, cereals, cattle and sheep) but production of those commodities with small trade volumes (barley, cattle and sheep) is relatively protected by the price inelasticity of demand. By contrast, those industries with much lower emissions intensities (vegetables, fruit (excluding grapes) and poultry) see relatively little impact from the emissions taxes, with price increases of around 2–3% relative to the baseline, and output falls of similar magnitude.

6.13.2 Scenario 2: 10% Reduction in Aggregate Agricultural Emissions, with End of Pipe Abatement

Introducing end-of-pipe abatement options in scenario 2 reduces the price in-crease from the emissions restriction in every agricultural industry compared to scenario 1 (Fig. 6.5). This is intuitive as emissions taxes are lower in scenario 2, and the value of the tax saving is instead invested in abatement equipment.

Thus while the immediate costs do not change between the two scenarios, in the first scenario they are lost completely to farmers as they go entirely to government, whilst in the second scenario a portion is converted into capital, and thus remains on the farm, lowering the emissions factor of future production, and hence the rate of future emissions taxes. The production results follow from those for prices, with

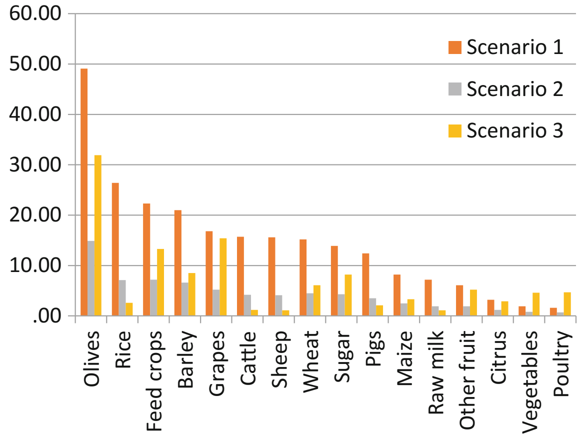


Fig. 6.5 Price changes relative to the baseline (%)

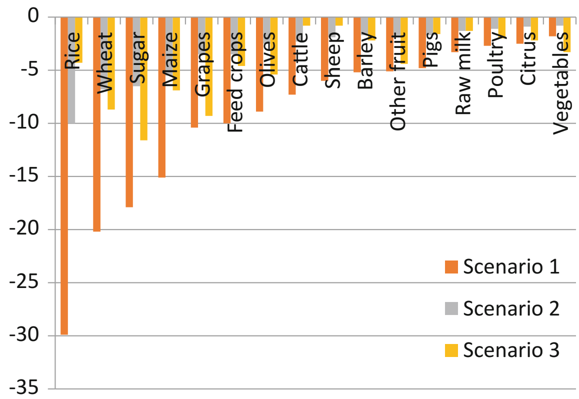


Fig. 6.6 Output changes relative to the baseline (%)

the falls in production in all sectors smaller than they were in scenario 1 (Fig. 6.6). On aggregate, the change in scenarios is not enough to reverse the pattern seen previously that composite crop production falls by more (5.7% in scenario 1) than that for livestock (4.7%). In scenario 2 these reductions in output have become 1.9% and 1.6% respectively.

6.13.3 Scenario 3: 10% Emissions Reduction in Each Agricultural Sector, with End of Pipe Abatement

Scenario 3 changes the picture quite significantly compared to that presented in the other two scenarios. The first thing to notice is that for the livestock sectors the effect of this scenario is a very small increase in prices relative to the baseline (Fig. 6.5). For two of these industries (cattle and sheep) this is because their 10% reduction target is non-binding (as noted above), meaning an emissions tax never emerges for these activities. They are thus able to take advantage of the falling cost of inputs resulting from other agricultural industries' shrinking production. This is true also of dairy cattle and poultry, the difference being that in these sectors the emissions target is binding.

In Spanish vegetable production, this activity exhibits a relatively low emissions intensity, although a high proportion of emissions comes from energy use, and thus is unable to benefit from end-of-pipe abatement. As a result a high emissions tax to force it to meet its target, and this does have an impact on price and output in this industry. The same is true of the fruit sectors which (with the exception of grapes) under scenarios 1 and 2 witnessed the smallest price and output effects. This has implications for Spanish policy-makers as fruit and vegetables are important export sectors—between them fruit and vegetables account for 30% of Spanish agrifood exports.

In the cereals sectors by 2020 the emissions tax generated by the cereals target in scenario 3 is higher than the uniform agricultural emissions tax in scenario 2. One consequence of this is that the cereals sectors undertake more end-of-pipe abatement than they did in scenario 2. As a result, the emissions factor attached to fertiliser use in these sectors falls even more in scenario 3, and the effect of emissions taxes on industry prices and output become less, as the emissions intensity of the industry falls. Thus by 2020, despite a cereals emissions tax in scenario 3 of €30/tCO_{2e}—higher than the agricultural emissions tax of €23/tCO_{2e} in scenario 2—the overall price increases of all cereals are smaller in scenario 3 than they are in scenario 2, as are the reductions in output. Emissions from cereals fall by more in scenario 3 than 2 as well, which suggests that over an extended time period, in this particular case, deeper emissions cuts are not necessarily more costly. Particularly if they are implemented at an early stage they may provoke abatement investment which, by reducing emissions factors, reduces the extent to which producers are penalised by emissions restrictions in later periods.

The overall effect of scenario 3 is to significantly reduce the burden of abatement in the livestock sectors, and share it evenly among all agricultural activities. Of course this means that the stringency of the policy is felt more keenly in those activities with either strong baseline growth or high costs of abatement.

Given the agricultural focus of this study, the focus here is on food prices, after noting from Table 6.6 that in scenario 1 the overall Consumer Price Index (CPI) rises 2% relative to the baseline, and this increase is 1.5% in scenario 2 and 1.6% in scenario 3. The same story is magnified in the aggregate food price index (Table 6.7), which (in comparison with the baseline) rises 6.1% in scenario 1, 2% in scenario 2 and 3.2% in scenario 3. The fact that food prices rise by more than the general price index, even when agricultural emissions benefit exclusively from end-of-pipe abatement options, is indicative of the high emissions intensities of most agricultural activities relative to the Spanish average. Looking at Table 6.7, in scenario 1 the biggest price increases are in the most emissions intensive sectors, namely olives and processed red meat (derived from cattle and sheep, which are both emissions intensive), whilst vegetables have a much smaller price increase. As noted above, the livestock sectors

Table 6.6 Macroeconomic results

Cumulative results in 2020	Baseline	Scenario 1	Scenario 2	Scenario 3
	% Change 2007–2020	% Relative to baseline		
Real GDP	1.8	−1.2	−0.9	−1.0
Real private consumption	−3.0	−0.8	−0.7	−0.7
Real investment	−39.8	−2.8	−2.5	−2.4
Real government spending	5.8	0.2	0.1	0.2
Real exports	64.3	−1.1	−0.7	−0.9
Real imports	−0.3	−0.5	−0.7	−0.6
Consumer price index	−0.9	2.0	1.5	1.6

Table 6.7 Household food prices relative to the baseline in 2020 (%)

	Scenario 1	Scenario 2	Scenario 3
Olives	28.0	8.9	18.7
Lamb	10.0	3.1	1.4
Beef	5.9	1.9	0.9
Poultry	4.3	1.7	2.2
Potatoes	4.2	1.8	2.8
Pork	4.0	1.5	1.8
Alcohol	4.0	1.7	2.9
Other fruit	3.9	1.5	3.5
Dairy	2.5	1.0	1.1
Other food	2.5	1.2	1.9
Citrus	2.3	1.1	2.2
Other crops	2.3	1.2	1.7
Vegetables	1.6	0.9	3.1
Sugar	0.7	0.6	0.7
Food index	6.1	2.0	3.2

benefit most from the addition of end-of-pipe abatement technologies, so a relative fall in the lamb and beef price when moving from scenario 1 to 2 is observed. Olives undergo a dramatic reduction in price be-tween the two scenarios, though they maintain the greatest price increase of all food commodities—indeed the general ranking of price increases is largely unchanged. This is not the case in scenario 3 where, although olives still show the greatest price increase by some distance, that for the red meat sectors in particular is greatly reduced (because cattle and sheep face no emissions tax in this scenario), whilst low emissions intensive products like fruit and vegetables now show the greatest price increases after olives. This is because of the high emissions taxes needed to force these expanding sectors to reduce their emissions by 10% in scenario 3.

Table 6.8 Household food demands relative to the baseline in 2020 (%)

	Scenario 1	Scenario 2	Scenario 3
Olives	−21.9	−8.1	−15.7
Lamb	−8.8	−2.9	−1.3
Beef	−4.5	−1.5	−0.7
Potatoes	−4.1	−1.7	−2.6
Poultry	−3.9	−1.6	−2
Pork	−3.6	−1.4	−1.6
Othfruit	−2.9	−1.1	−2.6
Ocrops	−2.6	−1.2	−1.7
Dairy	−1.8	−0.7	−0.8
Other food	−1.8	−0.9	−1.3
Citrus	−1.6	−0.8	−1.5
Vegetables	−1.4	−0.8	−2.7
Alcohol	−0.7	−0.3	−0.5
Sugar	−0.1	−0.1	−0.1
Food index	−4.1	−1.5	−2.1

The responses of household consumption to these price increases are shown in Table 6.8, and offer few surprises, with the biggest reductions in demand in olives and red meat, and the smallest in sugar. Calculating the ratio of percentage changes in household consumption by percentage changes in price—both relative to the baseline—gives an estimate of the 'general equilibrium' elasticities (Table 6.9). The generally higher elasticities in scenario 2 compared to scenario 1 are to be expected as price increases are smaller in the former. Of even greater interest though is the fact that the two commodities with the lowest elasticities of demand are alcohol and sugar—both of which have certain addictive qualities and are generally considered to be price inelastic.

6.14 Conclusions

This review of the use of computable general equilibrium (CGE) models in environmental policy analysis highlights four important strengths. Firstly, CGE models are versatile in that their macroeconomic grounding is ideally tailored to the analysis of economy wide environmental policy analysis and the assessment of different environmental policy options in terms of economic efficiency (for example, with and without revenue recycling), real incomes or even other sustainable development goals. Secondly, by incorporating dynamic economic mechanisms (i.e., savings-investment, capital accumulation, labour market adjustments), the temporal dimension of the model is improved. From the perspective of environmental policy, this enhances the analysis to accommodate the gradual introduction or withdrawal of policies (e.g.,

Table 6.9 Estimated price elasticities of demand of food products

	Scenario 1	Scenario 2	Scenario 3
Olives	−0.78	−0.91	−0.84
Lamb	−0.88	−0.94	−0.93
Beef	−0.76	−0.79	−0.78
Poultry	−0.91	−0.94	−0.91
Potatoes	−0.98	−0.94	−0.93
Pork	−0.90	−0.93	−0.89
Alcohol	−0.18	−0.18	−0.17
Other fruit	−0.74	−0.73	−0.74
Dairy	−0.72	−0.70	−0.73
Other food	−0.72	−0.75	−0.68
Citrus	−0.70	−0.73	−0.68
Other crops	−1.13	−1.00	−1.00
Vegetables	−0.88	−0.89	−0.87
Sugar	−0.14	−0.17	−0.14

switch from grandfathering to auctioning of permits; CAP and trade effects) and the indirect cumulative period-by-period impacts said policies may have on investment decisions and economic growth. A third advantage is the ability of CGE to deal with multiple pollutants (CO_2, CH_4, N_2O etc.) and policies. Given the well documented potential for reducing radiative forcing through abatement of these gases, and in particular their dominance in total agricultural emissions, these are crucial for a full analysis of abatement potential in the agricultural sector. Finally, we have also seen that such models are able to incorporate (in admittedly a stylized way), induced technical change in relation to end-of-pipe abatement options in the agricultural sector. The inclusion of marginal abatement cost curves calibrated to bottom-up data on the costs and abatement potentials of various technologies is a significant advance in improving the realism of climate change mitigation analysis. In the context of the agricultural sector, it enables a full picture to emerge of how emissions reductions may be distributed among agricultural sectors based on the abatement options available to them. Omitting this abatement potential could lead to an overestimation of the cost of achieving the mandated reductions in greenhouse gases.

The second part of the chapter employs a single country CGE model of the Spanish economy which incorporates (in different degrees) each of these analytical advantages to examine the impacts on the agricultural sectors under the auspices of the EU-mandated GHG emissions reductions targets for 2020. The scenarios examine (inter alia) how the incorporation of marginal abatement cost (MAC) curves affect the costs of GHG reductions in the Spanish agriculture sector. The inclusion of MACs induces a modest reduction in the macroeconomic cost of the emissions restrictions to Spain in terms of real GDP (1.2 and 0.9% lower than the baseline in 2020 without and with MAC curves, respectively). Focusing on the agricultural sector, the addition of MAC curves tend to concentrate emissions reductions in the livestock sectors as the data suggests they have access to more low-cost abatement options when compared with crops sectors. The emissions tax necessary to meet the 10% reduction target for agriculture as a ‘diffuse’ sector falls from €85/tCO_e without the MAC curves to €23/tCO_{2e} with, and the projected total direct cost to farmers of the policy (emissions taxes plus the cost of abatement equipment) falls by around 70%.

Policy-induced price increases and output reductions are reduced fairly evenly across all agricultural sectors, as the single emissions target for aggregate agricultural emissions means reductions can still be focused where they are cheapest. Thus the fall in output relative to the baseline is around 20% greater in livestock than that in crops, and this is a consistent result with or without the MAC curves.

In addition, the model is used to analyse two policy options for ensuring the agricultural emissions reduction target is met. The first (scenario 2) sets a single target for aggregate agricultural emissions, with a uniform emissions tax rate, and allows reductions to be distributed depending on the relative costs of abatement—analogous to a cap-and trade scheme among agricultural industries, with all permits auctioned at the market price. The second (scenario 3) divides agriculture into 10 subsectors and forces each of them to reduce their emissions by 10%. The results suggest that in scenario 2, as noted above, emissions reductions are concentrated in the livestock sectors, which allows certain key Spanish export commodities such as fruit, vegetables and olives, a degree of slack to increase their production. In scenario 3 this is no longer the case, and they become the agricultural industries for whom meeting the 10% target is the most costly. Indeed, a consistent pattern is that those industries which reduce their emissions by more than the average (10%) in scenario 2 face a less than average emissions tax (€23/tCO_{2e}) and vice versa. At the most extreme, for cattle and sheep farming, which has the largest reduction in emissions of all agricultural sectors in scenario 2, the 10% reduction target in scenario 3 is non-binding, resulting in a zero emissions tax.

In general the costs of the emissions restrictions in terms of welfare, real GDP and, particularly, agricultural output, are smaller in scenario 2 than scenario 3, lending support to the idea that there are efficiency gains from using a cap-and-trade scheme to focus emissions reductions where they can be made at the lowest cost. An important caveat is that the model does not account for the administration costs of running such a scheme, though it is a point of contention as to whether these would be significantly greater than those associated with ensuring each agricultural activity meets a specific emissions reduction target. Such a cap-and-trade scheme appears to work in conjunction with the trend in Spanish agriculture of a moderate expansion in certain key crop sectors relative to livestock. These crop sectors—particularly fruit and vegetables—are among the least emissions intensive agricultural products, so their expansion is likely to help Spain to meet its GHG targets more easily—though it may raise other environmental concerns beyond the reach of this study.

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Chapter 7
General Equilibrium Models: A Computable General Equilibrium Model to Analyze the Effects of an Extended Drought on Economic Sectors in México

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7.1 Introduction

The agricultural sector in Mexico is small in terms of its relative contribution to GDP, but significant in terms of its total employment. Overall, the primary sector, which includes agriculture, livestock and forestry accounts for only 4% of GDP but employs roughly 15% of the labor force. The agricultural sector is highly vulnerable to climate change due to the severe impact which higher temperatures and modifications in precipitation patterns can have on water availability and plant growth. Conversely, omissions from the agricultural sector can also contribute to climate change. The pumping of water for agricultural purposes, for example, is currently subsidized through low electricity prices, leading to both the overuse of electricity, (produced by fossil fuels) and the depletion of groundwater sources. Consequently, policies such as ethanol production have been promoted in Mexico with the stated goal of climate change mitigation.

The agricultural sector is thus seen as an important component of any climate change reduction and adaptation strategy. In this chapter, we evaluate the economic impact of various agriculture-related mitigation policies currently under discussion in Mexico. More specifically, using a Computable General Equilibrium (CGE) model, we examine strategies for increasing energy efficiency in water pumping and irrigation, substituting chemical for organic fertilizers, and promoting the use of biofuels based on agricultural crops, and evaluate their impact on GDP, sectoral production,

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consumption and social welfare for Mexico. Using land as a fixed input for agriculture and livestock, our CGE results show that some of these policies enhance economic growth and increase productivity in agriculture and livestock. We also find, however, that other policies neither promote economic growth nor lead to a decline in Greenhouse Gas (GHG) emissions.

The chapter is divided into three sections. In the first section we present the computable static general equilibrium model which we employ and address its appropriateness for this simulation exercise. In the second section we then describe the policies to be simulated, namely, the use of ethanol, bio-fertilizers and water efficient irrigation technologies. We then present our model's results and discuss the benefits of using CGE models as a tool to evaluate agricultural issues.

7.2 The Model

When simulating agricultural policies, a rather straightforward static CGE model has general advantages over a more complex dynamic model. First, the impact of agricultural policies are usually seen rather quickly, which is very much in line with the results given by a static model. Moreover, a static model is better suited to accommodate a fixed factor, such as land. In a dynamic model all production factors are required to grow at a given rate during the period analyzed. A static model, by contrast, has no such growth requirement and the productivity level of a fixed factor such as land need not change over the period analyzed.

Our model is national in scope and consists of producers, consumers, the government and a foreign sector (for an extended explanation, please refer to Elizondo and Boyd 2017). There are 12 producing sectors including primary activities (agriculture, livestock, forestry and fisheries), energy (mining, oil and natural gas, refining and electricity), and other activities, such as chemicals and plastics, manufacturing, transport, and services. The model's consumption sectors consist of food, household goods, consumption services, energy, private and public transport, gasoline, housing and water. Mexican households are divided into four representative agents, according to their level of income. The poorest agent, Agent 1, represents deciles 1 and 2, while the following three deciles are clustered into Agent 2. Agent 3 groups the next three deciles, and Agent 4 represents the top two deciles.

The model uses nested constant elasticity of substitution (CES) functions, and each of the model's production sectors is given by:

$$V_j = \varphi_j \left(\delta_{L,j} L_j^{\frac{\sigma_j - 1}{\sigma_j}} + \delta_{K,j} K_j^{\frac{\sigma_j - 1}{\sigma_j}} + \delta_{E,j} E_j^{\frac{(\sigma_j - 1)}{\sigma_j}} + \delta_{M,j} M_j^{\frac{(\sigma_j - 1)}{\sigma_j}} \right)^{\left(\frac{\sigma_j}{\sigma_j - 1}\right)} \tag{7.1}$$

where

V_j = value added for each sector j
L_j, K_j, E_j, and M_j = labor, capital, energy, and material inputs used in each sector j
φ_j = shift parameter
σ_j = elasticity of substitution between inputs,
δ = share parameters defined so that

$$\delta_{L,j}, \delta_{K,j}, \delta_{E,j}, \delta_{M,j} > 0 \tag{7.2}$$

and

$$\delta_{L,j} + \delta_{K,j} + \delta_{E,j} + \delta_{M,j} = 1 \tag{7.3}$$

Each of the four consumers have demand functions which reflect their actions in the economy. In the model, they maximize their utility subject to their income constraint, as shown in Eqs. (7.4) and (7.5),

$$U_c = U_c(X_c, R_c), \tag{7.4}$$

s.t

$$TG_c + TF_c + (P_L * L_c) + (r * K * S_c) = (INV * S_c) + (P_X * X_c) + (P_L * R_c) \tag{7.5}$$

U_c = household utility (nested CES functions)
X_c = consumption of goods and services per agent
R_c = leisure
TG_c = government transfers
TF_c = transfers from the foreign agent
P_L = wage
L_c = labor
r = rent from capital
K = capital
S_c = share of capital for each household
INV = total investment
P_X = price of goods

As mentioned above, there are four agents which are modeled according to their income levels. All agents are endowed with labor. The bottom half of the population in Mexico own no capital assets, at least not in the form of formal savings. Therefore, only the two richest agents (3 and 4) in our model own land and capital.

In order to appropriately simulate alternative agricultural policies, we modified the model to introduce land as a capital input. With that modification, the model can then consider the trade-off among competing promotion policies aimed at increasing production in the agriculture and/or livestock sectors by allowing for land use changes between crops and livestock. Prior models using land as a factor include Dixon et al. (2007) and Kretschmer et al. (2008), Banse et al. (2008), Hertel et al. (2008), Birur et al. (2008). Gurgel et al. (2008) and Reilly and Paltsev (2007) also integrate land use into their models by explicitly considering the conversion costs of changing land use. Our model follows Reilly and Paltsev's methodology and incorporates the primary factor shares given in the Hertel and Tsigas (2002) study.

The behavior of the government is analogous to that of consumers. Its income, however, is derived from taxes and tariffs. It then spends that income on goods and services (as consumers do) or in subsidies and transfers. Thus for the government sector we have:

$$U_G = U_G(X_G) \tag{7.6}$$

s.t.

$$\sum_{f=1}^{2} FTX_f + \sum_{s=1}^{14} T0_s + \sum_{d=1}^{9} TX_d + \sum_{s=1}^{14} TAR_s = (P_X * X_G) + \sum_{c=1}^{4} TF_c \tag{7.7}$$

U_G = government utility
X_G = goods and services consumed by the government
FTX_f = taxes to factors of production
$T0_s$ = taxes to production sectors
TX_d = taxes on consumption goods and services
TAR_s = tariffs on imports
P_X = goods prices
TF_c = government transfers.

There is also a foreign agent which produces and consumes goods and services in the form of imports and exports. Following Ballard et al. (1985), we posit an international "agent" and balance international payments, according to the Eq. 7.7 defined as:

$$\sum P_m * IM_j = \sum P_j * EX_j + \sum TF_c \tag{7.8}$$

P_m = price of imports
IM_j = volume of imports
P_j = price of exports
EX_j = volume of exports
TF_c = transfers from the foreign agent.

The model is calibrated for 2010 using data from various national and international sources (Ministry of Finance, The Mexican Central Bank, World Bank, among others). Our primary data source is the Mexican input-output matrix (INEGI 2003) and the National Survey of Mexican Household Income and Expenditures (INEGI 2010).

7.3 Policies and Results

Using the static computable general equilibrium model we conduct a series of counter-factual simulations examining the impact of biofertilizers, efficient irrigation and ethanol production. In each case we give a brief background and then describe the policy and the results.

(a) Agricultural Practices Policies: Biofertilizers and Efficient Irrigation

In Mexico, GHG emissions from the agricultural sector primarily arise from the overuse of electricity for water pumping, and the present system of planting and fertilization practices. Using our model, then, we simulate two policies that are related to a more efficient use of resources in the agricultural sector: (1) the use of biofertilizers and (2) the introduction of water-efficient irrigation technologies. The use of organic fertilizers, based on bacteria and fungi that coexist with plants, help to fix nitrogen from the atmosphere into the soil, reducing the need for chemical fertilizers which are more environmentally harmful and often costly and inefficient.

Irrigation policy can also be economically inefficient and environmentally dangerous. The agricultural sector accounts for roughly 80% of all the water used in Mexico while paying a zero price for this service. This itself leads to overuse of resources as well as allocation inefficiencies. At the same time, the electricity used for pumping services is heavily subsidized. This turns out to be distributionally regressive since the farmers who have access to wells and pumping are primarily those in the upper income brackets.

In our initial counter-fractural scenario then, we simulate the introduction of biofertilizers along with the promotion of efficient irrigation and water pumping technologies in agriculture. In order to finance the implementation of these actions, the subsidies currently applied to power for water pumping are redirected towards financing technologically efficient irrigation and pumping technologies. This policy can be expected to lower GHG emissions by reducing the use of electricity for pumping. Interestingly, at the same time, this reduces water consumption and protects groundwater tables, providing additional environmental benefits.

Results

Using a static CGE model we model the effect of biofertilizers use and efficient irrigation technologies on production costs. Because of lower energy use, lower water use and lower chemical fertilizer use, total costs go down. At the same time, these policies foster technological developments. Thus our model shows that aggregate GDP increases by 0.18% and social welfare goes up by 0.06%. Government welfare, however, falls marginally (−0.2%) since support to biofertilizers and efficient irrigation slightly exceed the savings from subsidy elimination (Fig. 7.1).

Our model also allows us to determine the welfare effects our simulations on the four different income groups. The agricultural policies tested in this exercise are progressive, and improve the welfare of the lower income groups relatively more than that of the higher wage earners. The progressiveness of this policy is primarily

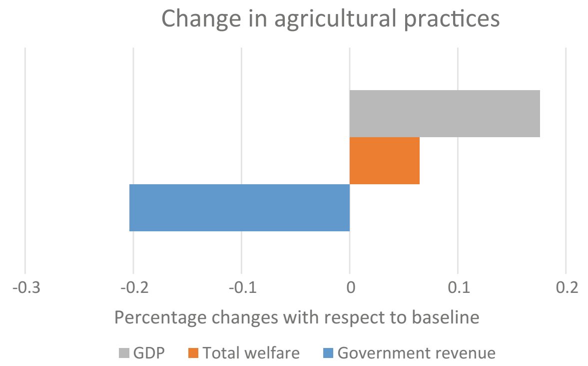


Fig. 7.1 Growth in GDP, government revenue, and total welfare (% change with respect to the base case scenario). Source: Own

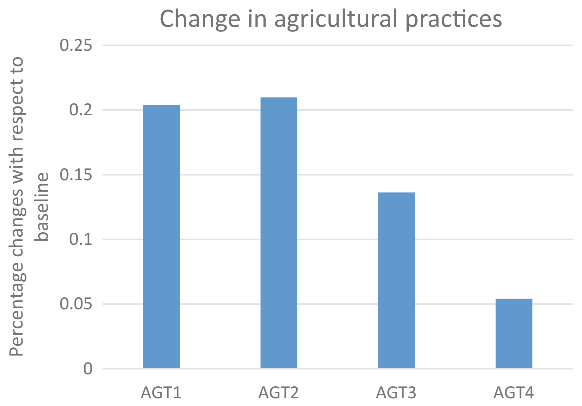


Fig. 7.2 Welfare impacts according to income groups (% change with respect to the base case scenario). Source: Own

due to a fall in the price of food since food expenditures take up a higher proportion of the lower income groups' budgets. Thus, these agricultural policies increase the relative welfare of the 50% of the population with lower incomes (Fig. 7.2).

Predictably, the largest output effects occur in the agricultural sector, where production increases 6% with respect to the base case. Livestock and manufacturing output are marginally increased (0.49 and 0.26% respectively) as animal feed prices decline, and new equipment is built for irrigation use. At the same time the elimination of the water pumping subsidy decreases the demand for electricity, while lower reliance on artificial fertilizers decrease the demand for their industrial chemical inputs (Fig. 7.3).

The increases seen in agricultural production have ripple effects in our model's consumption sector. The fall in the price of food leads to an increase in its intake and simultaneously frees income to be used for the consumption of other goods (Fig. 7.4).

Fig. 7.3 Changes in selected production sectors (% change with respect to the base case scenario). Source: Own

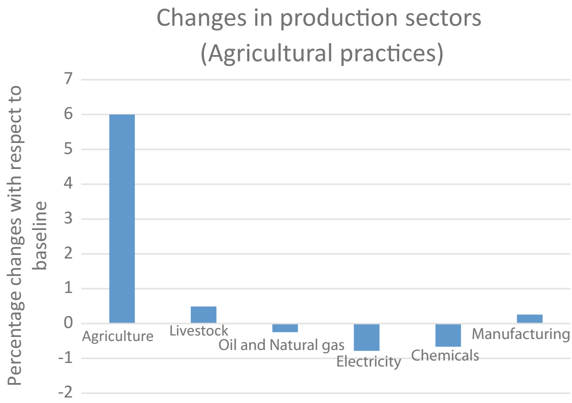
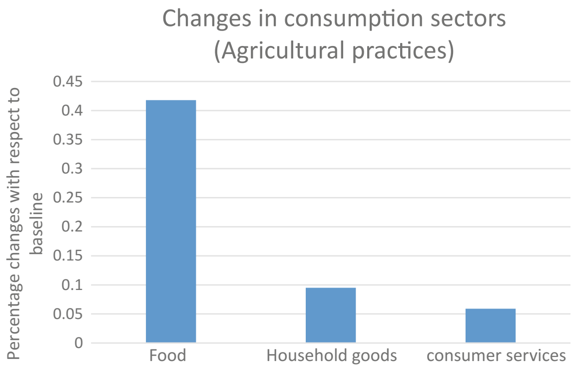


Fig. 7.4 Changes in selected consumption sectors (% change with respect to the base case scenario). Source: Own



Land Use

Finally, increased agricultural activity drives up the intensity of land use and increases the price of land relative to that of labor and capital. Thus we see that the price of land rises by 0.8% with respect to the price of labor and by 1.1% with respect to the price of capital.

(b) Agricultural Inputs for Biofuel Promotion: Ethanol Production

To simulate the economic impacts on ethanol production in Mexico we posit an initial situation where the economy does not produce ethanol, but where ethanol is poised to enter the economy. The ethanol sector is defined as a slack activity, inactive in benchmark, but reactive to those changes in relative prices which would initiate its production. For this task, we modified the social accounting matrix (SAM) so as to introduce ethanol as a latent sector.

If ethanol were to be competitive with gasoline then it would be used as a substitute and mixed in with gasoline prior to its delivery in gas stations. Ethanol then is modeled as an input into the refining process, which, in turn, lowers the need for gasoline from petroleum. Hence, the choice to use ethanol is made at the refinery level rather than by individual consumers at the pump.

At present, Mexico does not have official data on ethanol. Consequently, we relied on data from Brazil following the input-output work done by Guilhoto and others (Guilhoto and Filho 2005, 2010; Martínez et al. 2013), and scaled up their coefficients to reflect Mexican supply costs (which were inferred from previous bidding processes to produce ethanol). Ethanol is expected to be domestically produced, and hence trade is expected to be affected only to a limited degree.

When the biofuel promotion law was enacted (2008) and the first tendering processes took place, the results were disappointing. This bidding process did, however, provide us with useful information on the size of the gap between Pemex's willingness to pay and the minimum income required by the bidders. Policy makers generally agreed that a subsidy was needed to promote production. The government, however, was unwilling to provide the financial resources required at that time.

In our model the production of ethanol is activated by means of a subsidy since subsidies are needed up to the point to where ethanol becomes competitive with gasoline. Local prices were estimated according to the results of the 2011–2012 PEMEX tendering process.

Results

For this scenario, the use of a slack activity in our CGE model allows us to identify the effects of the introduction of ethanol into the energy mix. The subsidy needed to promote the use of ethanol has a slightly negative effect on aggregate GDP (0.04%), government revenues decrease (0.35%) because of its additional outlays on subsidies, and all of these effects combined result in a decrease of total welfare by 0.05% (Fig. 7.5).

The top half of the income distribution, represented by agents 3 and 4, do well under this policy. They receive additional benefits consistent with the fact that they own capital in the model. On the other hand, the poorest consumers, agents 1 and 2, suffer welfare losses since food prices rise, and food represents a significant share of their expenditure (Fig. 7.6).

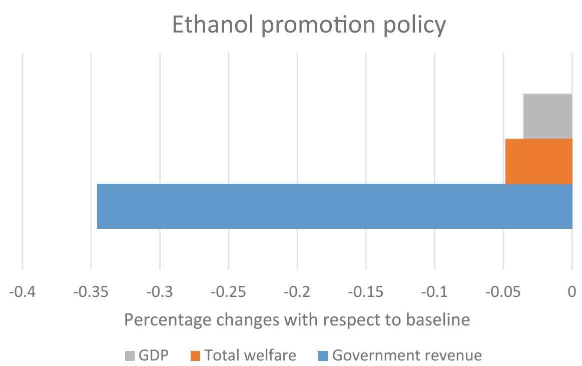


Fig. 7.5 Growth in GDP, government revenue, and total welfare (% change with respect to the base case scenario) Source: Own

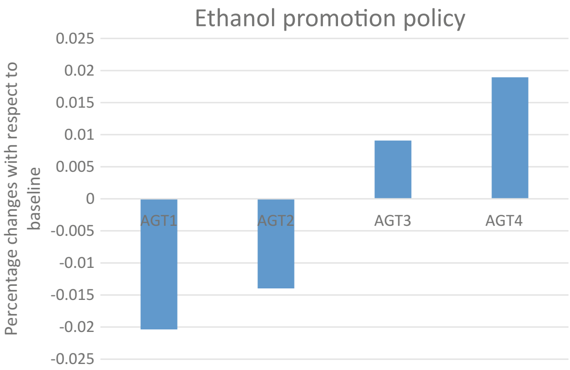


Fig. 7.6 Welfare impacts according to income groups (% change with respect to the base case scenario) Source: Own

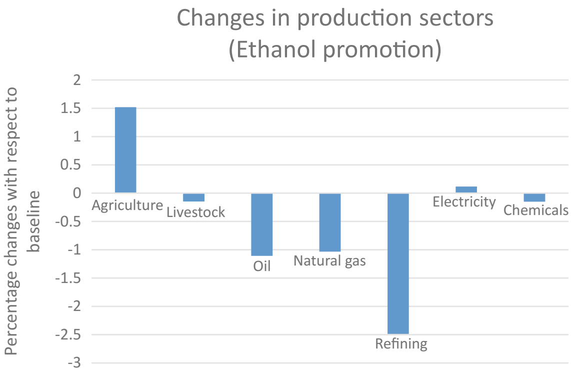


Fig. 7.7 Changes in selected production sectors (% change with respect to the base case scenario) Source: Own

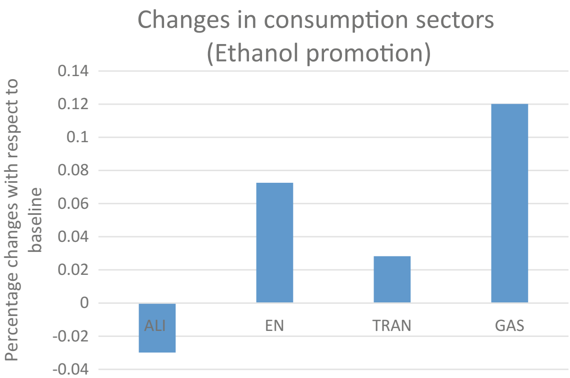


Fig. 7.8 Changes in selected consumption sectors (% change with respect to the base case scenario) Source: Own

Implementing an ethanol promotion policy has a slightly negative effect on the aggregate economy, since an inefficient policy is subsidized. There is a redistribution of resources to agriculture, lowering the output of refining products, oil, and natural gas. Some producers gain, however, and the largest gains are, not unsurprisingly, seen in agricultural production (Fig. 7.7).

An ethanol promotion policy incentivizes the expansion of crops and negatively affects livestock production since less land is now available for grazing purposes, and, even though agricultural production increases, the consumption of food as a final product declines a bit. Other consumption sectors are only marginally affected, but it is worth noting that overall gasoline consumption increases as consumers increase their demand in response to lower relative prices (Fig. 7.8).

Land Use

Since a policy of ethanol promotion relies on crop subsidies it comes as no surprise that production goes up in the agricultural crop producing sector. The chief concern for ethanol opponents however has been that agricultural output would be displaced towards the production of energy. Our results show that subsidizing the use of ethanol decreases the land available for livestock and reduces livestock production. Thus, even though total agricultural output increases, the consumption of food slightly diminishes as agricultural production is diverted to energy use. Finally, we see that a higher demand for land increases its price 1.5% relative to both the price of capital and the price of labor.

7.4 Conclusions

Static computable general equilibrium models are a useful tool to analyze agricultural policies because they are able to treat land as a fixed resource as well as to capture the linkages across sectors. These are details which are important to include in the analysis since land is essential to agricultural production and activities in the agricultural sector have economy wide repercussions.

The production of food and livestock in Mexico are socially important since they provide work for a large share of the poorest households in the country. Their contribution to GDP however is somewhat limited, as the outcome of all these policies reveal. Our results show that there are indeed policies which would promote consumer welfare, increase the contribution of these sectors to the economy, and enhance climate change mitigation targets in Mexico. Other policies, such as ethanol promotion, however, may lower economic output a bit, and, at the same time, be distributionally regressive.

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Chapter 8
Costs and Benefits of Adaptation: "Economic Appraisal of Adaptation Options for the Agriculture Sector"

Paul Watkiss and Alistair Hunt

8.1 Introduction

Climate change has the potential to lead to major effects in the agriculture sector, including changes to production, with potentially negative effects (e.g. from lower rainfall or increasing variability) but also potentially positive effects (e.g. from CO_2 fertilization, or extended growing seasons) from changes in mean weather variables, as well as changes in the risks of extreme events, shifts in the range and prevalence of pests and disease, etc. These will lead, in turn, to effects on aggregate production, supply chains, prices and trade. There are also possible risks to food security and the breakdown of food systems (IPCC 2014).

However, many of these impacts can be reduced through adaptation. There is therefore an increasing interest on the costs and benefits of adaptation actions, and a corresponding growth in the evidence base of studies at different aggregation scales for the agriculture sector (OECD 2015a). This evidence includes:

- Global assessments of adaptation costs and benefits of adaptation in the agriculture sector, including macro-economic analysis. These estimates provide information on global-level costs and benefits of adaptation and inform international negotiations relating to adaptation finance.
- National studies, which undertake similar analysis to the global assessments, but at the country level. These are potentially relevant for national adaptation strategies and agricultural sector plans, providing information on the possible financing needs for adaptation, and the costs and benefits of national level strategies. These include

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studies in both the OECD and developing countries, the latter particularly linked to initiatives related to emerging international climate finance.
- Sub-national and local analyses, including disaggregation at the farm level, which focus on very specific responses for adapting to climate change, and which include detailing of the costs and benefits of various options.

This chapter provides a review of this evidence base, outlining the methods and insights at these various spatial scales, and identifying future research priorities.

8.2 Previous Reviews and Methodological Framing

There has been a gradual evolution of the information base on the costs and benefits of adaptation in the agriculture sector over recent years, as reported by a succession of reviews. An early review of the costs and benefits of adaptation (OECD 2008) identified that agriculture was fairly well covered in relation to the benefits of adaptation, but much less so on the costs. The dominance of studies on adaptation benefits was confirmed in a later review (Agrawala et al. 2011), though this also identified the emergence of some global adaptation investment cost studies for agriculture. The IPCC 5th Assessment report on the economics of adaptation (Chambwera et al. 2014) reported a greater number of cost-benefit studies including macro-economic assessments for agriculture, and finally, the review of the ECONADAPT project (ECONADAPT 2017) identified a number of studies on the costs and benefits of adaptation at multiple scales.

Importantly, the later reviews (Chambwera et al. 2014; ECONADAPT 2017) also identified changes in the methodological approach to the analysis of the costs and benefits of adaptation over time. This relates to two key factors. First, there are a range of different methodological approaches that have been used for assessing the costs and benefits of adaptation in the agriculture sector. Some of these are appropriate to the particular aggregation level, but also reflect different framings or objectives. Second, there is a focus most recently on adaptation studies that provide support to decision makers and take account of uncertainty, especially at the local to national scale. These studies move to the provision of information for adaptation plans and decisions.

Early analysis in this field tended to focus on adaptation benefits, using two main approaches. The first approach undertook simulation modelling using crop productivity models (e.g. Parry et al. 2004) and generally considered only the increased use of irrigation and fertiliser to address changing yields (sometimes complemented with autonomous market adaptation in relation to trade) from future climate change. The second approach used econometric (Ricardian) analysis (e.g. Seo et al. 2009; Kurukulasuriya and Mendelsohn 2008) to assess the historic relationship between climatic factors and land value or farm net revenues, and then used these relationships to look at likely farm responses under future climate change.

A subsequent set of studies emerged that focused on adaptation costs, usually referred to as investment and financial flow (IFF) analysis. These have been implemented at the national to global scale. These studies used a different approach that assessed existing agricultural sector investment and financial flows, and then estimated the increase needed (the adaptation cost) to cope with climate change (e.g. McCarl 2007). These usually derive estimates by applying a generic adaptation 'mark-up' on current investment/finance levels that is judged to be sufficient to reduce impacts effectively (Agrawala et al. 2011). These studies have the advantage of grounding the analysis in current policy and plans, but they have a less direct link to future climate change, and importantly, they do not quantitatively assess adaptation benefits.

Subsequent studies have focused more on economic analysis of costs and benefits. The earlier frameworks for assessing the costs and benefits of adaptation (see Metroeconomica 2004) centred on scenario-based impact assessment. This first assesses the change in climate (using climate model projections) and then assesses the physical impacts and economic costs of climate change that are projected to occur. It then assesses the potential benefits of adaptation in reducing these impacts, and finally, the costs of this adaptation. This information can be used to assess the economic effectiveness of adaptation, i.e. whether the economic benefits of adaptation outweigh the costs and even the optimal response. It can also be used to compare alternative adaptation options. It is noted that in this framework, there is a residual impact of climate change after adaptation: the most effective (or optimal) level of adaptation will therefore be a balance between the costs of adaptation, the benefits of adaptation and the residual impacts (OECD 2015a).

This framework has been advanced in a number of ways, and particularly with the use of simulation (crop modelling) studies, either extending impact studies to look at subsequent adaptation costs and benefits, or taking the results of these models and putting them into an economic model. At the local scale, the results from farm-level models (which typically yield or other farm variables) can be linked with economic models (separate models or combined bio-economic models), and then a series of adaptation options considered. At the national and international level, the outputs from these bio-physical simulation models can be used in trade models or Computable General Equilibrium (CGE) models (e.g. OECD 2015b), the latter to allow analysis of the impact at scale and across the economy, for example, how changes in agricultural production affects prices and how changes in the agricultural sector cascade through to other sectors of the economy. These models can then be used to look at possible adaptation responses, particularly with respect to trade.

However, all of these methods—and the resulting estimates from their application—use a so-called science first, impact assessment methodology. There are a number of problems with this approach, especially for informing adaptation decisions. First, there is a major challenge arising from the appropriate treatment of uncertainties when assessing the costs and benefits of adaptation (Wilby and Dessai 2010). This includes both scenario (emission pathway) and climate model uncertainties. Including these uncertainties in an adaptation decision framework leads to a major difference in the framing and methods, compared to an approach that utilises individual projections and uses an if-then [predict impacts and optimise adaptation response] framework, effectively stripping out the incorporation of these uncertainties in the decision process.

Second, and related to this first argument, there is a body of literature (e.g. UNFCCC 2009) that identifies the fact that impact assessment studies are unlikely to be very useful for informing practical adaptation decisions. This is because they are highly stylized and have insufficient consideration of immediate and short-term timescales of relevance for early adaptation, they do not consider wider (non-climatic) drivers and existing policy, and they focus on a narrow set of technical adaptation responses (as these are easier to incorporate in the modelling framework). There is therefore a set of more recent economic studies that either apply decision making under uncertainty (DMUU) (Watkiss et al. 2014) or focus on practice orientated analysis for adaptation (Groot et al. 2014).

Third, there is a recognition that adaptation involves economic prioritisation challenges, because the (more substantial) impacts of climate change—and thus adaptation benefits—primarily arise in the longer-term. Early action to address longer-term risks will incur costs in the short-term, but provide benefits much later: these long-term benefits are small when assessed in net present value terms (i.e. as discounted future benefits). This leads to a greater focus on short-term low regret adaptation measures and the more careful selection of early action to address long-term climate change considering uncertainty and discounting (OECD 2015a).

In developing countries, a further issue has emerged around the current adaptation deficit (defined in the AR5 as the gap between the current state of a system and a state that minimizes adverse impacts from existing climate conditions and variability). There is an additional need to consider whether this existing adaptation deficit has been assessed in studies, and to ensure these gaps are addressed first, otherwise planned future orientated adaptation will be less effective (Watkiss et al. 2015). These methodological issues are considered in the review of adaptation costs and benefits presented below, to provide the context to methods and results. We review studies at the different aggregation levels that they adopt, highlighting the differences in methods that result from adopting.

8.3 Global Studies

Early work on the global costs of adaptation focused on the near to medium term (2020–2030), using IFF analysis. The most comprehensive of these was the UNFCCC (2007) study. The agricultural sector analysis (McCarl 2007) used an IFF methodology, estimating adaptation costs (research, extension and irrigation) as \$14 billion/year globally in 2030, of which 50% was in developing countries. However, a critique by Parry et al. (2009) considered this to be a significant underestimate since it included coverage of only a limited number of crops.

IFPRI (2009)—supporting the global EACC World Bank Study in their Economics of Adaptation to Climate Change (World Bank 2010a) study—assessed the potential global costs [in developing countries] of adaptation in the agricultural sector using a global agricultural supply-and-demand projection model (the International Model for Policy Analysis of Agricultural Commodities and Trade, IMPACT) linked to a biophysical crop model (DSSAT) and estimated adaptation costs (in the period 2010–2050) at approximately US$ 7 billion/year [for developing countries]. This study used an impact assessment approach to estimate the economic costs of climate change, then estimated the costs of adaptation to achieve pre-climate change levels of welfare (i.e. so that there were no residual impacts above the baseline). The EACC summary (World Bank 2010a) provided an updated global estimate of US$2.5–3 billion/year for adaptation costs for the agriculture sector in developing countries (the costs between 2010 and 2050 for adapting to an approximately 2 °C warmer world by 2050). The study reported that agriculture was a low proportion of total adaptation costs (which for all sectors in all developing countries, were estimated at 70–100 billion/year). The study explained that this finding was due to the fact that although there were significantly lower crop yields and production under climate change (especially for irrigated and rain-fed wheat and irrigated rice), adaptation costs were low because economic welfare impacts were compensated by the counteracting effect of trade. However, as outlined below such an assumption may be challenged when considered from a practical and ethical perspective. Furthermore, national level analysis in the same EACC study indicates that these global estimates are likely to be a significant underestimate (see next section).

Ignaciuk and Mason-D'Croz (2014) also used the IMPACT model, and a similar approach to the IFPRI study, to estimate annual adaptation costs in agricultural research and development and in improved irrigation technology for OECD countries. The analysis explored the potential effects of climate change on yields and prices, then analysed the potential impacts of two sets of adaptation strategies on yields, prices and food security, which were: (i) research and development (to develop new crop varieties that are better suited to changed climate conditions) and (ii) changes in irrigation technology. It provides estimates of the magnitude of adaptation costs for OECD countries, estimating these at between USD 16 and 20 billion per year by 2050. This is much higher than the estimate for all developing countries in the World Bank study (above paragraph).

There have been several global studies that assess adaptation costs and benefits using partial equilibrium models. As an example, Mosnier et al. (2014), estimated global adaptation costs of between 12 and 119 billion USD per year in 2050—depending on climate change scenario adopted. More recent studies have also factored in uncertainty and robustness to such global assessments (e.g. Leclère et al. 2014), including uncertainty with stochastic modelling, (Fuss et al. 2011, 2015), as well as expanding the list of options to include climate smart agriculture, in order to see how this affects costs.

There are also several global studies have used computable general equilibrium models (CGEs) to look at the global costs and benefits of adaptation, including market driven autonomous adaptation as well as planned adaptation. Wojtek et al. (2016) assessed market driven (autonomous) adaptation to look demand and supply reactions to changes in relative prices using a global multi-country, multi-sector CGE model

(CAGE-GEME3), which included an analysis of the agriculture sector. The analysis assessed how market driven adaptation could reduce potential climate change damages. It considered three key responses: labour mobility, both across sectors and region; the degree of substitutability between capital and labour in the production function; and the degree of substitutability for trade flows and domestic production. At the global level, the study found that market-based adaptation reduced climate change damages by approximately a third (compared to a case without adaptation) for both GDP and welfare losses (or gains). The analysis also undertook a more detailed analysis of Europe, and investigated the effects by region. Within the EU, the welfare-enhancement effect of adaptation is smaller at lower latitudes in the agriculture sector. The greatest benefits are in the UK & Ireland, followed by Northern Europe and the Central Europe North regions. These differences reflect the initial size of impacts as well as the potential for substitution (especially for agriculture).

Parrado et al. (2016) similarly used a global CGE modelling analysis which considered planned public adaptation including increased demand for irrigation to address agricultural impacts. The analyses focussed on how planned adaptation increases public expenditure and affects public budgets, considering climate related public goods, such as information acquisition and dissemination on likely extreme events, and protecting public and private assets at risk. The study included increased demand for irrigation services to reduce climate change impacts—extending an existing CGE model to consider land supply structure/rents and conversion of rain-fed land, as well as the additional costs that farmers face when they decide to expand irrigation. In the baseline (with climate change), lower latitude countries were found to be the most negatively affected in terms of decreased crop production and lower GDP. Under the adaptation scenarios, irrigation expansion reduces productivity and GDP losses and is considered an effective option (especially for lower latitude countries), though converting rain-fed into irrigable land is costly and increases agricultural prices, which prevents demand expansion. The overall macro-economic effects were small, since agriculture is a low contributor to value-added and GDP, though international trade effects also influence this result, as regions with lower increases in domestic prices (compared to world prices) export more, relatively. The analysis found that climate change—and the planned adaptation response—will thus reallocate crop production from more to less affected sectors/countries, and from developed to developing countries, assuming that the latter have relative advantages from lower irrigation costs.

The main adaptation options included in many CGE studies are trade, shifting crop types and land-use expansion. These studies highlight that looking only at crop yield projections is inadequate to derive reliable conclusions about the scale of climate change impacts and adaptation, and the same applies for national studies, (see next section). They find that international linkages through trade and commodity prices have a major influence on the effectiveness of adaptation planning with a strong influence on the profitability of agricultural production. However, the trade assumptions in all these trade, partial and general equilibrium models are considerable, as they project that some regions and countries will address climate impacts (and adapt) through large-scale shifts to imports. These changes are normally assumed to be frictionless, and they do not take into account the full implications of declining national production, the costs borne by local farmers or the wider multi-functionality and cultural aspects of agriculture in livelihoods and the economy. They also do not take into account current domestic agricultural production policy, the risks of food insecurity and the balance of domestic demand, and they do not reflect current agricultural trade policy or trade barriers adequately. Perhaps more importantly, they ignore equity and global justice issues associated with climate change adaptation, particularly when low income countries are affected, i.e. why should low income countries impacted by climate change use imports to address food production declines from climate change caused by the OECD. They are therefore likely to overestimate the adaptation potential and underestimate costs.

All the global estimates of adaptation costs are critically dependent on the climate change costs that arise in the first place, i.e. the damage costs before adaptation. The global impacts differ significantly according to the scenario and climate model, the impact model, the economic model, and other key assumptions, notably CO_2 fertilisation (which generally has a positive effect on yield). This can be demonstrated by recent analysis on the global impacts of climate change on agriculture undertaken in the Agricultural Model Inter-comparison and Improvement Project, (AGMIP), reported in Rosenzweig et al. (2013) and Nelson et al. (2013). The latter compares the outputs of seven economic models—three economy-wide (general equilibrium) models and four agricultural market-specific (partial equilibrium) models—from simulations that use the yield output to 2050 for a common climate scenario (RCP8.5) and a common reference socio-economic scenario for population and GDP (SSP2). The model inter-comparison also used seven scenarios of biophysical crop yield changes under climate change—based on a combination of five different crop models and two general circulation models. The analysis highlights the large differences that result in terms of production, changes in land production, trade and prices, even within a single simulation run. The implications for the appropriate design of adaptation strategy are therefore complex.

Finally, it is highlighted that the general use of impact assessment methods in the studies above means that there is little consideration of uncertainty (i.e. models agree a large degree of perfect foresight) and they also omit opportunity, transaction and implementation costs for agricultural adaptation. Including these aspects would increase costs. Set against this, the assessments also focus on market and technical adaptation, and thus exclude other options, which may mean some low cost options are excluded.

8.4 National Studies

Similar methods to the global analysis have also been applied at the national level.

A set of agricultural sector investment and financial flow studies of early adaptation costs were undertaken at the national level for costs to 2030 as part of the UNDP IFF initiative (UNDP 2011) for Bangladesh, Colombia, Ecuador, Gambia, Liberia, Namibia, Niger, Paraguay, Peru, Togo, Turkmenistan and Uruguay. The adaptation costs for agriculture in these 12 country UNDP IFF assessments totalled $3 billion/year in 2020 rising to $6 billion/year in 2030, though a high proportion of these costs were in Bangladesh. The total costs are high when compared to the earlier global IFF estimates (McCarl 2007) as well as the global trade model results. This can be explained partly by the different methods, assumptions and coverage. The detailed IFF studies are grounded in current national policy and they include a much greater coverage of risks as they look to build resilience across all existing policy areas. They also have a more realistic assessment of current costs and therefore the possible costs associated with delivering additional subsequent adaptation—including implementation and policy costs, and costs disaggregated between private and public sectors. They may also include some costs for action that are targeted at reducing the existing adaptation deficit, they are often focused on irrigation options (which are costly), and they exclude the potential for international trade, all of which would lower costs.

A second set of national studies was undertaken alongside the EACC World Bank Study. This includes detailed country studies in Bangladesh, Bolivia, Ethiopia, Ghana, Mozambique, Samoa, and Vietnam (World Bank 2010b, c, d, e, f, g) which all considered agriculture. These studies primarily used crop simulation models, but provided new insights through some consideration of uncertainty, and the linkage to economy wide models, with adaptation provided through research and irrigation. As an example, the country study in Ethiopia (World Bank 2010e) estimated high baseline costs of climate change (especially for rain-fed irrigation) and found that adaptation could reduce welfare losses by around 50%. The costs of adaptation and the residual impacts (together) for this one country alone were estimated to be $1.2 billion to $5.8 billion per year (for the period 2010–2050), though the study highlights different options could reduce these costs. This can be compared to the global EACC study, which estimated that the global costs of adaptation for agriculture would only be US$2.5–3 billion in total, highlighting that even if lower cost options are available at the national level, there is still a large disconnect between the country and global estimates.

A further study—the UNFCCC NEEDS project in Egypt, Ghana, Jordan, Lebanon, Maldives, Mali, Philippines, Nigeria (UNFCCC 2010)—assessed the short- and long-term costs of adaptation financing needs, including in the agriculture sector. These studies also indicate high individual country estimates, though the studies use different methods and time periods and so lack comparability in absolute terms.

There have also been a large number of other regional and country level initiatives on the costs and benefits of adaptation that include agriculture. These include studies in Bangladesh (ADB 2014). Brazil (Margulis 2010), Bhutan (ADB 2014), Caribbean (CCRIF 2010), Central America, China, Ethiopia (FDRE 2014), Ghambia (AIACC 2006), Kenya (SEI 2009), India (Markandya and Mishra 2010; ADB 2014), Indonesia (ADB 2009), Maldives (ADB 2014), Nepal (ADB 2014), Philippines (ADB 2009), Rwanda (SEI 2009), Samoa (ECA 2009), South Africa (AIACC, 2006), Sri Lanka (ADB 2014), Thailand (ADB 2009), Uganda, and Vietnam (ADB 2009). Most of these studies use some form of simulation-based crop models, some using subsequent trade or CGE modelling. As examples, in India TERI (2010) estimated costs of adaptation to 2050 for agriculture at $1.4 billion per year, while the analysis in Brazil (Margulis 2010) estimated adaptation costs from genetic modification at $1 billion a year in research investment.

There are also studies in Europe and the Americas that make preliminary estimates of adaptation costs, using a variety of approaches, e.g. in Sweden (SCCV 2007), the Netherlands (de Bruin et al. 2009), Canada (NRC 2007; NRTEE 2011) and the US (Sussman et al. 2014). However, all these studies are subject to the same issues as highlighted above, namely the use of future orientated scenario-based impact assessment, the focus on technical adaptation and absence of detail regarding the applied decision context. At the national level, other constraints also start to become apparent, such as—for example—cross-sectoral competition for water: studies that include these cross-sectoral aspects (e.g. Iglesias et al. 2012), either due to competition for water, or from environmental limits on fertiliser use, find current policy constraints would reduce adaptation levels and/or increase adaptation costs.

More recently, the focus has switched to costed national adaptation plans, aligning to national or sector development planning or national adaptation plans. These seek to identify adaptation options and short-term adaptation needs, aligned to the development of sector development implementation (e.g. the next 5 year medium term sector plan). As an example, Tanzania (GoT 2014) produced an Agriculture Climate Resilience Plan, 2014–2019, which set out the costed adaptation (and mitigation) options over this period at $126 million.

The move towards national sector planning and development is also leading to a new framing towards mainstreaming adaptation. Mainstreaming is the integration of climate change (adaptation) into national, sector and local development policy and plans, rather than implementing standalone climate plans or projects (OECD 2015a). There is a focus therefore on integrating adaptation, and estimating incremental adaptation costs, for country-based medium-term sector agricultural development plans and investment plans. This places adaptation within the current planning and policy context and builds on current activities; it can—however—sometimes lead to a focus on the short-term, at the expense of early action to address longer-term (and more major) climate change.

8.5 Local Studies

The final section focuses down on local scale adaptation, i.e. sub-national and local, down to the farm level. Unsurprisingly, this literature is more focused on generating verifiable estimates of the costs and benefits of adaptation options. A first set of studies look at standard agronomic options such as changing sowing dates, planting new cultivars or varieties, or changing management practices. These are often already implemented as reactive measures—as farmers experience climatic change, they adjust. There are also a large number of generic agricultural development activities that are sometimes included in such analysis, although these are not climate specific (i.e. improved agronomic management, better pest and disease control, enhanced access to finance, improved market information and supply chains, etc.). These improve farmers' resilience in general terms, but do not target climate metrics. These results report high economic benefits from agricultural adaptation, though as highlighted by the IPCC (Porter et al. 2014) while agronomic adaptation improves yields, the effectiveness is highly variable, and differs for crops and regions.

In recent years, the focus has been on farm level options that more explicitly address current climate risks (from climate variability and extremes) and build resilience for the future, i.e. climate smart agriculture (CSA) (FAO 2013). These are forms of sustainable agricultural land management (SALM) practices that improve soil water infiltration and holding capacity, as well as nutrient supply and soil biodiversity. They include options such as agroforestry and intercropping, soil and water conservation, reduced or zero tillage, and use of cover crops or crop residues. These reduce current climate related risks from rainfall variability and soil erosion, increase soil organic matter and soil fertility, increasing productivity, and reduce greenhouse gas emissions by reducing soil emissions or preventing more emission intensive activities. These contrast with more traditional measures to increase productivity, such as fertiliser use or increased irrigation, which have the potential for negative externalities.

There has been analysis of the costs and benefits of these climate smart agriculture options. In the OECD, examples included qualitative benefit:cost assessment for a range of climate smart agriculture initiatives in Canada (British Columbia 2013). There has also been an analysis of the costs and benefits of conservative/low tillage in Germany (UBA 2012), though this found benefit to cost ratios were low and uncertainty was high (noting it also reported low B:C ratios for irrigation).

In the developing country context, there has been much more analysis of these options, because of their potential for supporting rain-fed agriculture and avoiding high irrigation costs. These CSA measures provide immediate productivity benefits, see Branca et al. (2011). The costs of these measures have also been reviewed in detail by McCarthy et al. (2011). Specific examples of cost-effectiveness assessment and even cost-benefit analysis also exist (e.g. Branca et al. 2012 in Malawi: ECA 2009 in Mali), and these studies generally report that climate smart options are win-win for food security and climate change adaptation, as well as providing mitigation (reduced GHG) benefits. Some options lead to direct co-economic benefits, e.g. agroforestry can generate additional income streams from fuel wood, building material and food. In general, there are high benefit:cost ratios reported for these options and they are often selected as early adaptation priorities, including under future climate change (e.g. ECA 2009; Lunduka 2013). Ex ante economic analysis (Ferrarese et al. 2016) of the International Fund for Agricultural Development's Adaptation for Smallholder Agriculture Programme (ASAP), has provided information on the benefit to cost ratios of such options. This programme provides grants for additional climate change investments over and above the main investments of the country loan for agricultural development, focusing on delivering low-regrets options (investments and capacity building). It reports high benefit to cost ratios of between 1.1:1 and 7.2:1 for interventions, from an analysis of projects across 32 countries.

However, McCarthy et al. (2011) highlights some critical issues about CSA options. First, there is high variation in costs per hectare between sites, i.e. transferability is important (see also Kato et al. 2009). The estimates for investment and maintenance categories vary widely depending on the specifics of the situation, reflecting the large differences among regions, agro-ecological conditions, pre-project land uses, household asset endowments, and the differences in cost structure of the various types of activities considered. Second, and perhaps more important, many of these climate smart options have important opportunity and transaction costs. These include opportunity costs of labour and land, as well as up-front cash outlays that are a barrier to poor farmers. For example, some options take-up land and thus forego crop income in the short-term. Even if opportunity costs are negative over the longer-term horizon, it is important to consider these in the short run as they are certainly an important barrier to adoption, particularly in subsistence economies or to poor farmers (who generally have the highest opportunity costs). The costs and benefits also vary with assumed discount rate, noting that some options, such as soil improvement or agroforestry, take several years to establish benefits, while costs are borne immediately, thus only becoming profitable in the long run: they therefore do not tend to perform as well under CBA as some conventional measures (e.g. Shiferaw and Holden 2001), and require lower discount rates or ancillary benefits to appear more economically attractive. In relation to farm uptake, some of the economic benefits are not accrued to local farmers (e.g. economic benefits of lower GHG emissions). Estimating costs is also difficult, especially when markets are not perfect (or informal) and labour is mostly supplied within the household. The bottom line is that promoting and implementing various climate smart-techniques is likely to more costly than some of the figures currently cited in the literature, especially for the poorest producers, who are perhaps the most important to reach.

There is also some interesting work on the differences between single options and portfolios of options. As an example, Di Falco and Veronesi (2012) found that the most promising low-regret options provided largest benefits (i.e. they are most effective in increasing net revenues) when they were implemented as portfolios, rather than on their own. As an example, the positive impact of changing crop is significant when coupled with water conservation strategies or soil conservation strategies.

There has been a focus on other early low- and no-regret options. There are also a growing number of studies that look at enhanced weather and climate services (short-term forecasts to seasonal forecasting) for agriculture, which show high benefit to cost ratios for these options (e.g. Clements et al. 2013) and which build future resilience to climate change. There has also been studies to identify other early adaptation options (no- and low-regret), such as the UK (Wreford and Renwick 2012; Moran et al. 2013). Promising options identified in such studies include increasing water supply through on-farm storage reservoirs and incentivising efficient water management, the introduction of soil conservation measures and increasing expenditures on research and development. Recent analysis (Porter et al. 2014) reported that some adaptations (e.g., cultivar adaptation and planting date adjustment) were (on average) more effective than others (e.g., irrigation optimization). Crop switching was also found likely to have high benefit to cost ratios in Germany (e.g. UBA 2012).

There is debate, however, as to whether irrigation should be considered an early low- or high regret option for agriculture. Whilst some studies highlight these options as low regret, (e.g. IPCC 2012), others disagree (Ranger and Garbett-Shiels 2011), notably when viewed from the perspective of cross-sectoral water demand and up-front capital costs.

There are related studies that consider agriculture and irrigation in areas of extreme water scarcity. Notable studies include the early work in Australia (Howden et al. 2003), which highlighted the high benefit to cost ratios of R&D to improve the evidence base, and the more recent focus on vulnerable areas such as the Murray—Darling Basin (Adamson et al. 2009; Connor et al. 2009). The latter found that relatively low cost adaptation strategies are available for a moderate reduction in water availability and thus costs of such a reduction are likely to be relatively small. In more severe climate change scenarios higher costs are projected to result. Adaptations predicted include a reduction in total area irrigated and investments in efficient irrigation. A shift away from perennial to annual crops is also predicted as the latter can be managed more profitably when water allocations in some years are very low.

Finally, there is also the potential to assess the costs and benefits of adaptation using decision making under uncertainty (DMUU) methods. The application of these techniques has not primarily been focussed on adaptation in the agriculture sector, though there are some relevant examples. Thus, there is a study of the application of real options analysis—a method that allows analysis of the trade-off between acting now versus waiting and acting in the future when information reduces climate and other uncertainties—to agricultural irrigation in Mexico (World Bank 2009). There have also been applications of robust decision making (RDM)—which test options across a large number of plausible futures using monte-carlo simulation methods to identify those which perform well over a wide range of scenario futures—for example with a RDM application for agriculture in Nigeria (Mereu et al. 2018). There has also been progress towards more iterative risk management in agricultural adaptation. The UK ECR (Frontier 2013) developed adaptation pathways (called roadmaps) for the agricultural sector. These identify early options that focus on building the enabling environment and information for adaptation in the farming sector, i.e. they move away from the technical optimisation of early studies towards research, awareness, information provision, best practice and addressing barriers. Similarly, an iterative risk management approach was also used in the Ethiopian Climate Resilience Strategy (FDRE 2014) and in recent adaptation projects in Rwanda (FCFA 2014).

8.6 Discussion and Research Priorities

This review presents a broad overview of the evidence base on the costs and benefits of adaptation in the agricultural sector. It serves to highlight that this literature has grown significantly, even in recent years, with estimates at all aggregation levels and across a large number of geographical areas.

At the global level, there is increasing analysis and insights for both market and planned adaptation, with the use of trade and economic models that complement crop simulation analysis. The results of these studies highlight the need for global assessments that consider the role of trade, since they have a major influence on the results compared with those studies that present crop yield projections in one region alone, absent of the smoothing influence of international trade. Indeed, these models find that market-based responses can significantly reduce climate change impacts at extremely low cost. However, further work is needed to investigate some of the assumptions that these studies include, which are thought likely to bias costs downwards—notably around the ease of production substitution, and the degree to which large changes in national production levels and imports reflect the reality of these changes, as well as the realities of international trade policy. There is also a need to investigate the full implications of some of these shifts, both in terms of the domestic costs or risks of higher trade flows (taking into account of issues such as the effects on rural livelihoods, the wider environmental benefits of agriculture, the greater risks of food price shocks, etc.). Some analysis of the moral and ethical assumptions implicit in these studies is also warranted, notably around whether developing countries that are affected by climate change resulting from more developed countries' emissions think it appropriate to increase imports as an adaptation response—especially given that this is likely to lead to higher residual damages, domestically. In addition, there is a need to better understand—through the use of validation analysis—why national studies lead to much higher adaptation costs than global studies, and to extend the range of planned adaptation options that are considered in modelling, especially if market-based adaptation is not as effective or cost-effective as currently modelled.

At the national level, the number of studies has also increased significantly over recent years, with a range of different modelling approaches in use. Many of the same insights from the global studies also apply at this scale. However, the larger number of studies provide a richer evidence base for inter-model comparison and analysis. Further work to better understand how impacts vary geographically and with other factors, and to understand the large variation in adaptation costs between methods, would be valuable. The most recent models have begun to extend the coverage of impacts and adaptation in the context of extreme events and have adopted more integrated analysis (e.g. of competition for water demand), and how this may change choice of adaptation options. Furthermore, recent studies have also started to better integrate adaptation in national agricultural development planning; further work to integrate adaptation costs and benefits into medium and long-term sector planning and investment would be extremely useful.

At the sub-national level, there is now a much larger evidence base on the costs and benefits of local adaptation, with a particular focus on climate smart agriculture. Whilst this is extremely promising, more work is needed to better understand how these options vary with context and location—in other words, their transferability—and also to better understand the real costs of implementation, including transaction, opportunity and implementation costs. There is also a need to develop the evidence base on the costs and benefits of soft, non-technical options, including capacity building, and to develop iterative approaches that allow early investment for longer lived investments and early climate change, as well as short-term climate variability. This includes further work needed to address uncertainty, with DMUU for project-based analysis, especially for major capital adaptation investments. Clearly, as this bottom-up evidence base expands, its findings can serve to better inform the specification of modelling in the more aggregated scale modelling.

This is a rapidly growing area, where there is still much to learn. In particular, there is an urgent need for more empirical studies to better represent the variety of adaptation options available in a given context, improve the treatment of climate—and other—uncertainties, and explore the reliability of transferring economic data between different locations and at different scales.

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Chapter 9
The Impacts of Climate Change on Crop Yields in Tanzania: Comparing an Empirical and a Process-Based Model

Pedram Rowhani, Navin Ramankutty, William J. Martin, Ana Iglesias, Thomas W. Hertel and Syud A. Ahmed

9.1 Introduction

Global food production will need to increase by 70–100% by the year 2050 to meet the higher demands of a larger population and higher per person consumption (Godfray et al. 2010; Foley et al. 2011). At the same time, growth in agricultural production will face substantial challenges due to a changing climate (Cline 2007). The international community is setting up important financial structures (Nakhooda et al. 2013) and mobilising large sums which need to be wisely used and effectively administered (Donner et al. 2011). Facing strong budgetary constraints, policy makers are under the additional pressure to select adaptation options that are well-targeted and have the highest impact. A wide variety of potential measures exist to offset the potential climate-related agricultural losses [e.g. improved irrigation infrastructure, better fertilizer management, crop variety changes, development of new heat resistant crops, (Vermeulen et al. 2012)]. Yet very little is known about the detailed climatic processes

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impacting agriculture in the future making it challenging to identify the appropriate adaptation strategy in different regions of the world.

Our current understanding of the impacts of climate change on crop yields re-lies either on statistical models relating historical crop yields to key climate variables like temperature and precipitation [e.g., (Schlenker and Lobell 2010; Lobell et al. 2011)] or simulation models trying to represent the various crop growing stages (Bondeau et al. 2007; Thornton et al. 2009; Deryng et al. 2011). In addition to uncertainties related to data, both methods have strengths and weaknesses (Hertel and Rosch 2010). Statistical crop models are scale dependent and constrained by the historical relationships (Lobell and Field 2007). Thus, they become unreliable in estimating future changes in yields when future conditions, especially farming practices and the climate, change significantly. And the relationships identified with these statistical crop models are only valid at the scale of analysis. Process-based crop models, on the other hand, are typically run at the field scale, require a large number of parameters, and run the risk of reproducing observed yields, while failing to correctly represent the processes involved due to over-tuning (Challinor et al. 2007).

Among the numerous uncertainties that influence many studies (Estes et al. 2013) there is now a clear understanding that structural differences between crop models need to be fully taken into account. However, most studies emphasise only differences between process-based models (Rosenzweig et al. 2013). Increasingly, inter-model comparison studies focus on differences between empirical and process-based modelling approaches (Maltais-Landry and Lobell 2012; Estes et al. 2013). Using this approach, a main objective of this paper is to investigate whether model structure plays a role in how different studies estimate the climate influence on crop yields.

A particularly important uncertainty lies in understanding whether crop yields are mainly influenced by temperature or precipitation in a specific region (Roudier et al. 2011). Studies based on process-based crop models report that changes in maize yields can be mainly explained by changes in precipitation (Andresen et al. 2001; Magrin et al. 2005; Twine and Kucharik 2009) whereas empirical studies report temperature as the main contributor to yield changes (Lobell and Field 2007; Kucharik and Serbin 2008). However, a comparison between these studies remains difficult since they use different modelling approaches and/or focus on different spatial and temporal scales. Looking at uncertainties in future climate predictions, a study found that temperature uncertainty was a greater contributor to yield uncertainty than precipitation uncertainty (Lobell and Burke 2008). Recently, the impacts of the interaction between temperature and precipitation on maize production in the United States through increased vapour pressure deficit influencing water stress were highlighted (Lobell et al. 2013). So, before policy makers can commit scarce resources to a given adaptation policy, it is critical to gain a better scientific understanding of how different climatic factors will influence yields.

In addition to methodological issues, the availability and accuracy of data al-so influence analysis. Unfortunately, poor data are a characteristic of many of the countries that are most vulnerable to climate change (Wood et al. 2014). Detailed and accurate data on crop yield at sub-national scales are often unavailable or difficult to access (Schlenker and Lobell 2010) with some recent improvements (Ray et al.

2012). Additionally, temperature and precipitation data at suit-able spatial and temporal resolutions are also lacking in many countries due to a dearth of weather stations (Washington et al. 2006; Challinor et al. 2007). This particularly affects precipitation data since precipitation is more localized and less easily interpolated than is temperature—especially in topographically variable regions (Price et al. 2000; Milewska et al. 2005; Alexander et al. 2006). Correctly assessing the future impacts of climate change on crop yields at local to regional scales also requires ac-curate and reliable climate projections. However, climate projections at these scales are hard to obtain and highly uncertain—particularly in the case of precipitation (Challinor et al. 2007). As a consequence, some models may project an increase in precipitation for a certain region while others predict a decrease.

The aim of this study is to provide insight into the differential impacts of temperature and precipitation on maize production in Tanzania using both an empirical model and a process-based crop model, using subnational crop and climate data. Recently, similar inter-model comparison studies were used to evaluate the historical impacts of climate on crop yields in the US (Maltais-Landry and Lobell 2012) and the ability of different models to predict crop suitability and productivity of maize in South Africa (Estes et al. 2013). These studies suggest that some process-based models such as DSSAT (Decision Support System for Agrotechnology Transfer) may be oversensitive to water (i.e., rainfall contributes less to crop yield when using an empirical approach) and empirical approaches estimate larger yield losses due to future climate change than the process-based model. Our analysis will focus specifically on comparing predictions from two different types of models for Tanzania maize yields in the context of changing temperature and precipitation. To this end, the results from a statistical model are compared to those generated from DSSAT which uses the Crop Environment RESource (CERES) group of crop models (Jones et al. 2003). Our analysis focuses on four key maize producing regions in Tanzania (Fig. 9.1) for which we have detailed data on production and harvested area, as well as monthly temperature and precipitation data.

This study does not consider fertilization effects of elevated atmospheric CO_2 levels. The statistical model does not allow us to directly estimate the impact of increased CO_2 levels (Lobell and Field 2007). The dearth of CO_2 experiments in tropical regions means we cannot satisfactorily model the impacts of CO_2 con-centration changes on maize yields in the process-based models. However, because maize is a C4 crop that is less sensitive to CO_2 (Parry et al. 2004; Leakey 2009), this effect seems likely to be small relative to that of temperature and precipitation.

9.2 Data

Crop data. In Tanzania, maize production is by far the most widely-grown crop, and is considered the main driver of the rural economy (Thurlow and Wobst 2003). Data on harvested area and production were acquired from the Tanzanian Ministry of Agriculture as well as from the Agro-MAPS dataset (available at

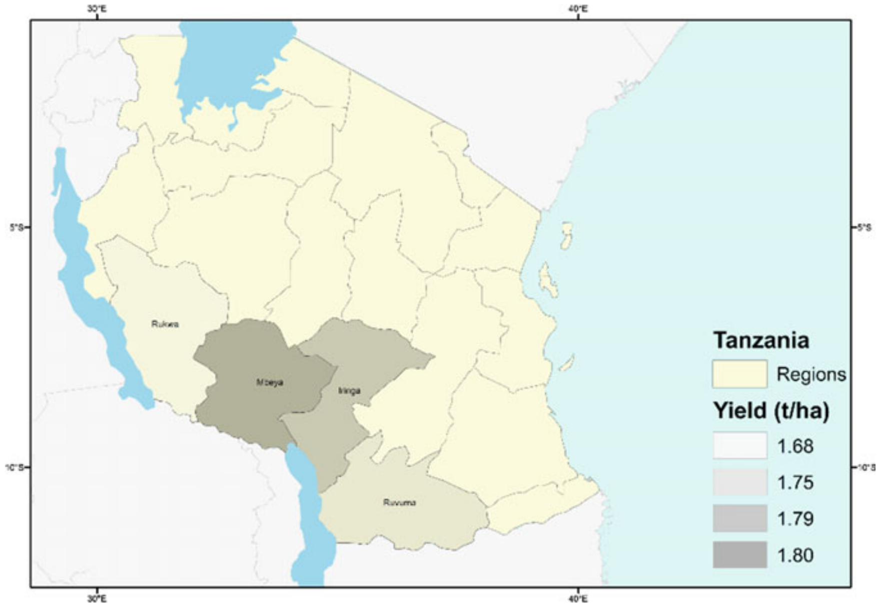

Fig. 9.1 **Study area**: This study focused on the four regions of Tanzania (grey shades depicting yields) with the highest yield in maize over 1992–2005, with an average production of 1.1 million tonnes per year and yield of 1.75 tonnes/ha

http://kids.fao.org/agromaps/). The data covers all four regions studied here and represent the period from 1992 to 2005. These data were converted to yields (tonnes/ha).

Over the studied time period, Tanzania produced on average more than 2.1 million tonnes of maize per year and yields fluctuated greatly around an average of 1.3 tonnes/ha. Iringa and Mbeya in the southern highlands are the most important maize producing regions in Tanzania (Bisanda et al. 1998). These two regions account for a quarter of the national maize production, producing on aver-age more than 700,000 tonnes each year. Other important maize producing regions are, in descending order of production, Shinyanga, Rukwa, Ruvuma, and Arusha. We based our analysis on the regions with the highest yields (Iringa, Mbeya, Rukwa, Ruvuma), which together constitute 55% of total maize production in Tanzania, with an average production of 1.1 million tonnes per year and yield of 1.75 tonnes/ha (Table 9.1). The reported yields in maize highlight considerable year-to-year variability over the 1992–2005 period (Fig. 9.2). Maize yields were significantly lower in the years 2000 and **2005**.

Climate data. In our previous study (Rowhani et al. 2011) we showed that more commonly used gridded climate data (i.e., Climate Research Unit available at www.cru.uea.ac.uk) only use a very limited number of weather stations in these regions and thus poorly represent spatial patterns over the region and substantially influence any analysis relying on such information. Similar to that study, we used the spatially-interpolated historical climate data from the Tanzania Meteorological Agency

Table 9.1 Regional average yield, harvested area, and contribution to the national production of maize over 1992–2005

Region	Harvested area (ha)	Yield (tonnes/ha)	National production (%)
Iringa	229,745	1.793	14.39
Mbeya	180,643	1.801	10.89
Rukwa	127,243	1.685	7.82
Ruvuma	115,693	1.747	7.49

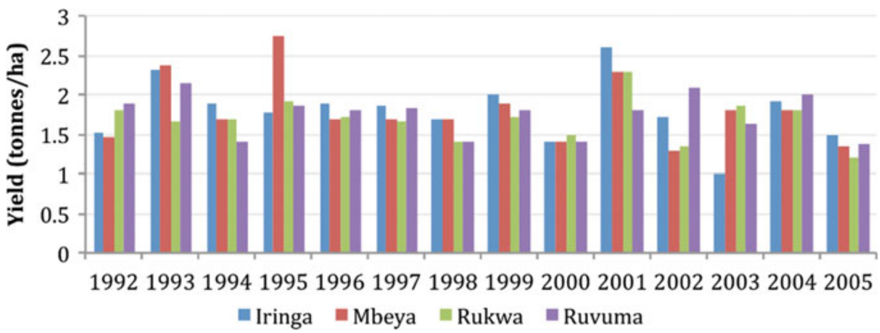

Fig. 9.2 Historical yields: The temporal dynamics of observed maize yield from 1992–2005 for all four regions of Tanzania

recording monthly minimum and maximum temperatures, and rainfall at 20 weather stations across the country. For the statistical model we used growing season (January to June) averages in temperature and precipitation.

On average, the four regions in the South received about 108 mm/month of precipitation during the growing season over the studied time period (Fig. 9.3). There are sharp de-creases in precipitation from 1996–1997 and 1999–2000 that may be related to warm and cold ENSO events during these years. The temperature records also show large inter-annual variations with 1993 witnessing substantially lower values (Fig. 9.3). The average seasonal temperature over the 14-year period in these four regions is ~22 °C.

The process-based model requires daily minimum and maximum temperature, precipitation and solar radiation. Some studies use simulated weather data based on the location of the studied site (Lobell and Burke 2010). We developed our own daily temperature and precipitation data using observed monthly data to correct model simulated daily data (i.e., NCEP/NCAR Reanalysis II), following (Ngo-Duc et al. 2005). Daily solar radiation data were also derived from the same model simulations, but remain uncorrected since we do not have monthly observations on this variable. This kind of inconsistency is unavoidable during bias correction unless the correction is done within the modelling framework itself (and we do not have access to that).

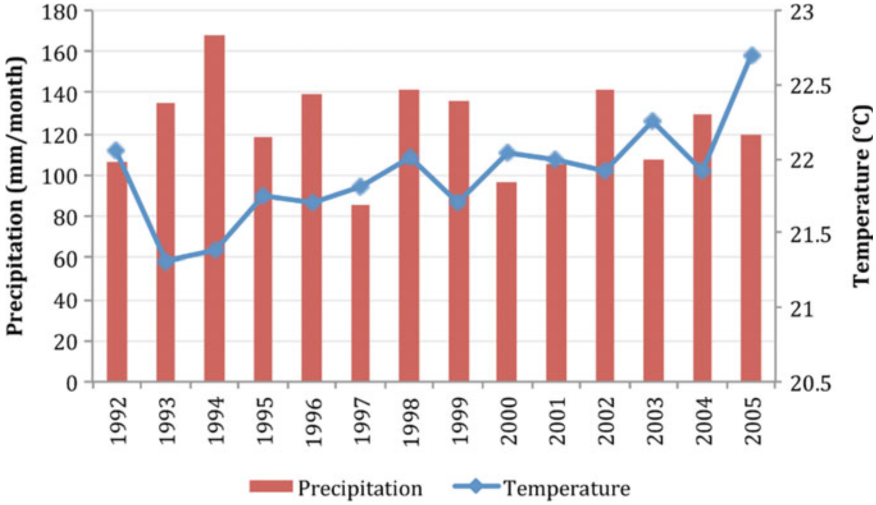

Fig. 9.3 **Historical climate**: Monthly growing season (January–June) precipitation and temperature from 1992 to 2005 averaged over the four regions in figure 1

However, yield variations are mostly driven by temperature and rainfall variations and this bias is unlikely to alter our findings.

Future climate projections for the SRES A2 scenario from 22 different global climate models (GCMs) analyzed by (Ahmed et al. 2011) were used to estimate changes in temperature and precipitation by 2050. For each model, we measured the difference in the average growing season monthly temperature and precipitation between the periods 1992–2005 (with the base climate representing the year 2000) and 2035–2064 (representing the year 2050). These changes in temperature and precipitation between 2000 and 2050 were then used to perform model simulations in order to assess their impacts on crop yield (see below).

The 22 GCMs simulate that, in 2050, the monthly mean temperature between January and June will increase on average by 1.4 °C (avgTmean), with a maxi-mum of +2.1 °C (maxTmean) and a minimum of +0.9 °C (minTmean). By 2050, changes in seasonal precipitation range between −16% (minP) to +19% (maxP) compared to the 1992–2005 average, with a mean of +5% (avgP). However, since some models predict an increase and others a decrease in seasonal precipitation, we separated them into two groups. GCMs simulating an increase in precipitation show an average of +8.1% (avgP+) increase for the January-June period by 2050. On the other hand, the models with decreasing precipitation estimate an average decrease of −5.3% (avgP−) by 2050.

9.3 Methods

Process-based model. This study draws on the well-established and widely used process-based model CERES-Maize as implemented in DSSAT to evaluate the impacts of changes in climate on maize yields (Jones et al. 2003). This model requires a number of weather, soil and crop management inputs.

A single model simulation was run for each of the four regions of Tanzania that were part of this study. For each of the regions, model parameters were calibrated to match the average historical yield data for the years 1992–2005, and by minimizing the percent model error (calculated as the root mean square error divided by the mean observed yield). Planting dates were automatically set based on soil moisture calculated by the model (volumetric soil water content at 30 cm depth between 60 and 100%) and soil temperature (between 10 and 40 °C), and found to be reasonable in comparison to information on usual planting dates in these regions (Bisanda et al. 1998). We applied very little fertilizer (5–10 kg/ha of inorganic nitrogen as ammonium nitrate) at the beginning of the planting sea-son to represent current practices (Bisanda et al. 1998). Rainfed conditions were modelled (only 3.3% of Tanzanian cropland was irrigated as of 1999; earthtrends.wri.org). The choice of cultivar substantially influences yields. This study uses a medium-short growing-season type of maize (described by the genet-ic coefficients in the CERES-Maize model: P1 = 280.0 P2 = 0.320 P5 = 700.0 G2 = 638.0 G3 = 6.40 PHINT = 38.90) that is typical for these regions. The crop was sown at planting densities typical of smallholder farmers of the region, at 3.3 plants/m^2 (Bisanda et al. 1998). Finally, model simulations started about 60 days before the expected planting date in order to equilibrate soil water content and temperature. Crop growth models require layered soil-profile characteristics that are often not adequately provided in regional or global soil datasets. In this study, we used reanalysed soil profiles from the ISRIC-WISE dataset (Romero et al. 2012). The calibration was done for each of the four regions separately resulting in a percent model error of ~25% across all four regions (Fig. 9.4).

Once all the parameters were calibrated, CERES-Maize was run for each region over the 14-year period from 1992 to 2005 using the observed base climate data. The average modelled crop yield over this 14-year period was taken as the baseline reference period (and referred to as the year 2000) for each region. Based on the future climate projections provided by the 22 GCMs, the temperature and precipitation inputs were modified within the Environmental Modification section of DSSAT in order to run climate change simulations over this same 14-year period. In other words, the 14-year period was repeated, but with predicted climate changes added to the observed base climate. While this 14-year period includes a strong ENSO event (1997–98), our simulation includes this bias in the future climate also as the climate changes are added as anomalies to the base climate for the climate change simulation. Since the GCM data only provided monthly-average climate, we assumed that each day within the month would witness the same changes in climate as the monthly average. As a consequence, our simulations will not be able to measure the impact

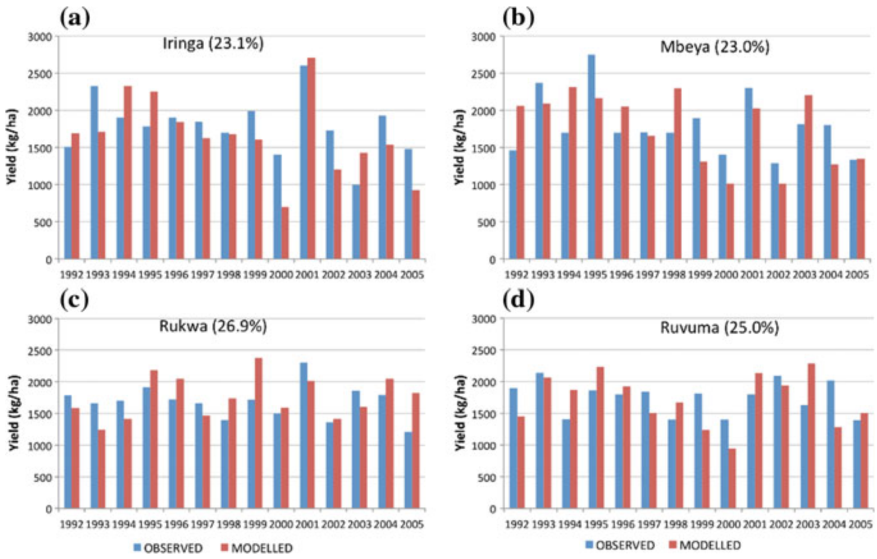

Fig. 9.4 Observed versus modelled crop yields: Comparison of observed and modelled crop yields for **a** Iringa, **b** Mbeya, **c** Rukwa, and **d** Ruvuma. The percent model error (calculated as the root mean square error divided by the mean observed yield) for each region is provided in parenthesis

of changes in diurnal variability, and may thus underestimate the impact that rainfall changes have on crop yields if the frequency is declining during key stages of the growing season.

Statistical model. For comparison, the results from the process-based model were com-pared to those obtained from multiple linear regression models (Eq. 9.1). Since this study only focused on the climatic impacts, and since the process-based model only simulated climate change effects, a time variable (Year) was also used in these linear models to capture yield changes related to non-climatic factors, especially technological development:

$$y = b0 + b1 * T + b2 * P + b3 * P2 + b4 * T2 + b5 * P * T + b6 * Year + \varepsilon \quad (9.1)$$

with b1–b6 representing the coefficients, and P and T being the precipitation and temperature over the crop growing season. These linear models were developed using stepwise model selection based on the Akaike Information Criterion (AIC) wherein the results were weighted using harvested area.

Table 9.2 Estimation of the current (Base) maize yields (in kg/ha) for the four regions by CERES-Maize and sensitivity analysis of the impacts on yields of an increase by 8% in precipitation, a decrease by 5% in precipitation, and an increase of 1.41 °C in temperature

	Iringa	Ruvuma	Rukwa	Mbeya
Base (2000)	1646	1744	1776	1773
avgP+ (+8%)	1897	1867	1975	2200
avgP− (−5%)	1366	1675	1624	1462
avgT_{mean}(+1.41°C)	1467	1533	1601	1680

9.4 Results

CERES-Maize model simulations. The climate change simulations using the CERES-Maize model are based on these changes in temperature and precipitation as shown by the 22 GCMs (Table 9.2). The CERES-Maize model was run over the same 14-year period but with an increase of 8.1% (avgP+), a decrease of 5.3% (avgP−) in precipitation, and an in-crease in temperature by 1.41 °C (avgTmean). Focusing on the GCMs showing an increase in precipitation by the year 2050, the average modelled crop yield shows an increase in yield by 0.3 tonnes/ha over all the regions (+14%). However, if we use only the GCMs that present a decrease in precipitation then the average modelled yield decreases by 0.2 tonnes/ha (−12%) over the main maize-producing regions. Finally, all GCMs show an in-crease in temperature that on average reduces yield by 0.2 tonnes/ha (−10%).

Additional climate change simulations were performed using the other future climate estimates, i.e. minTmean, maxTmean, avgP, minP, and maxP. A linear regression line was then fitted to these results to estimate yield sensitivity to temperature and precipitation changes (Fig. 9.5). These estimates were compared to the results from the multiple linear regressions.

Statistical model estimates. Using historical data, the results of the statistical analyses show that seasonal changes in precipitation and temperature have a significant impact on maize yields in Tanzania (Table 9.3). As expected, higher temperatures are detrimental to yields while increasing precipitation favours yields -although the relationship between yield and precipitation is non-linear as shown by the inclusion of the squared precipitation variable. The fit of the model over the four regions indicates that there are many omitted variables, as the R2 = 0.22. The estimates suggest that an increase of 1 °C will reduce yields by 5.8% while a rise of precipitation by 10% from the current baseline improves yields by 6.1%.

Comparison of the two models. For the 1.4 °C projected increase in temperature (avgTmean) by 2050 for the four regions of Tanzania, the climate change simulations within CERES-Maize (Fig. 9.5) show a decrease in crop yields by ~10% (Table 9.3). Changes in precipitation (AvgP+ and AvgP−), however, have a more important impact on crop yields, increasing or decreasing yields by ~16% or ~10% respectively.

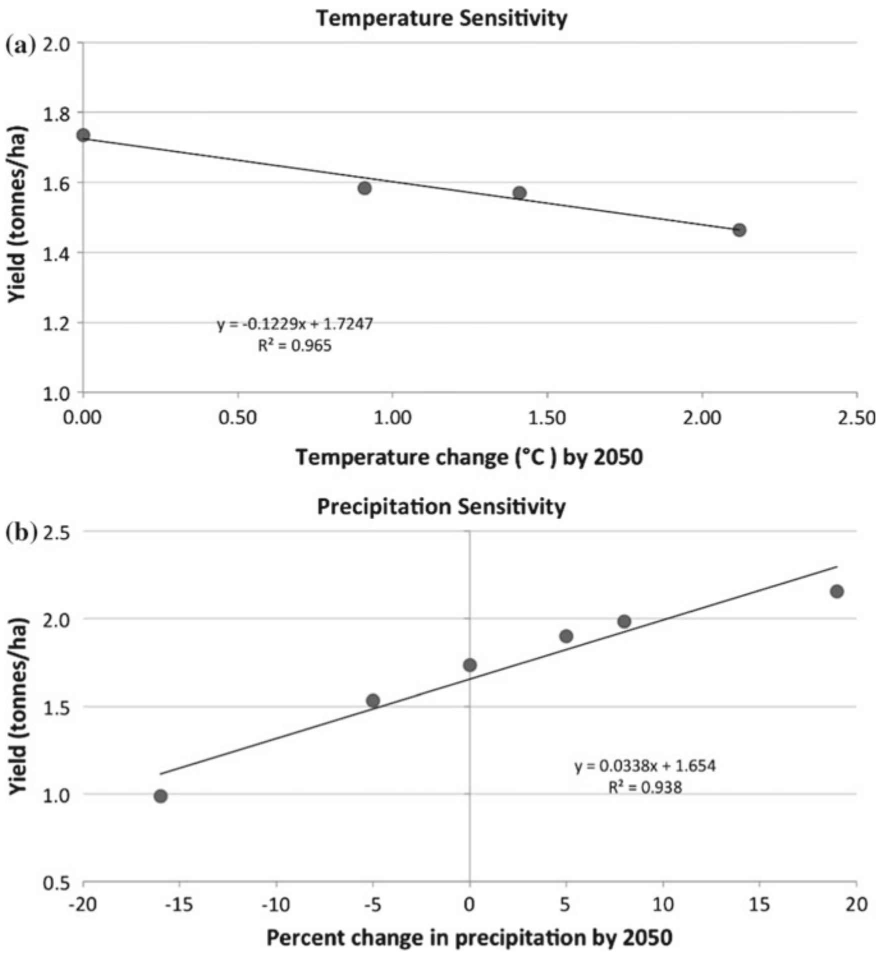

Fig. 9.5 Trends in yield impacts (in tonnes/ha) with future climate change over the four regions: Impacts of changes in temperature, in °C (**a**) and in percent precipitation (**b**), based on CERES-Maize. The sensitivity experiments were based on the range of GCM-simulated changes in temperature (no change baseline, avgTmean, minTmean and maxTmean) and precipitation (no change baseline, avgP, avgP+, avgP−, minP, and maxP)

For the same climate change scenario, by comparison, the statistical model estimates yield losses of around 8% for an increase in temperature, but precipitation changes have a less important influence on crop yields. Compared to the statistical models, CERES-Maize is more sensitive to precipitation, estimating similar yield im-pacts from changes in temperature and precipitation.

Table 9.3 Comparison table showing the impacts on maize yields of changes in temperature and precipitation by the year 2050, using either a process-based (CERES-Maize) or a statistical model

	$AvgT_{mean}$ (+1.41 °C) (%)	AvgP+ (+8%)	AvgP− (−5%)
CERES-Maize	−10.1	+16.3	−10.2
Statistics	−8.2	+5	−3.5

9.5 Discussion and Conclusions

Previous studies have shown considerable differences in crop response to climate change as simulated by various models (Tubiello and Ewert 2002; Palosuo et al. 2011; Asseng et al. 2013; Estes et al. 2013) and there is a need to reduce these disparities by improving our understanding of biophysical processes and the mathematical models that describe them (Soussana et al. 2010). In this study we highlight some of these differences by comparing the results of a process-based crop model to a statistical model analysing the impacts of temperature and precipitation on maize production in Tanzania (Table 9.4). Our study shows that the empirical model is overall less sensitive to changes in temperature and precipitation than the pro-cess-based model and that, depending on the chosen modelling approach, temperature may have a higher or lower impact on crop yields than precipitation, assuming all other factors remain constant (soil properties, management, genotype).

The models used in this study have their specificities and limitations (Hertel and Rosch 2010; Lobell and Burke 2010; Rötter et al. 2011). The scale at which the analysis is performed can influence the robustness of the results. CERES-Maize is a farm-level process model specifically designed to represent crop variations at the scale of a farm. However, there is a need to standardise and generalise this model at larger scales (Thornton et al. 2009). Similarly, statistical models have been shown to better perform at larger, provincial or country scales, a scale at which these models are often used (Lobell and Burke 2010). Recently, these models have, however, been used at more site-specific studies.

All models contain uncertainties and simplifications. In addition to the issues related to the availability and quality of data, models need to be accurately set up and represent key processes. In our case, we were interested in understanding the role of different climate factors on crop yields and we know that both temperature and precipitation are important to crop growth. Yet precipitation is a more localized phenomenon than temperature and a low spatial density in weather stations may lead to an underestimation of its real impact, relative to temperature, in a larger scale analysis (Gifford et al. 1998). This is especially true for statistical models which are more commonly used at these scales (Lobell and Burke 2010). The statistical model performance is highly dependent on revealed relationships between climate and yields in the data itself (as it has no process representation), and it may not be able to capture the covariance between the higher spatial (and temporal) variability of precipitation and crop yields. This is consistent with our results where our statistical model shows greater yield sensitivity to temperature compared to the process-based model. The process-based models, on the other hand, may not capture some of the non-linear responses of yields to temperature (Estes et al. 2013) which have been statistically revealed when detailed data were available (Schlenker and Lobell 2010). Only a few studies using process-based crop models include the direct effects of extreme heat on key phenological stages such as seed set and leaf senescence (Challinor et al. 2005; Moriondo et al. 2010; White et al. 2011). Adding the fact that the climate models are more unambiguous in their predictions about temperature, providing robust information to policy makers on whether to focus on irrigation rather than developing heat resistant crops in a given region may prove more challenging.

One important limitation of the CERES-Maize model may be its inability to adequately simulate the evolution of soil moisture (Maltais-Landry and Lobell 2012). Similar to that study, continuous multi-year simulations of CERES-Maize (using the same daily weather data of a given year over 14 years) show a persistent decline in soil moisture, suggesting an excessive drying of soils and thus impacting crop growth. This may be due to an over-estimation of the modelled evapotranspiration (ET) (Maltais-Landry and Lobell 2012). Aside from a variety of causes identified by these authors some factors in the water balance may also be poorly represented, such as runoff or drainage. In order to reduce the impact of this modelling bias the soil moisture conditions were reset every year in our model (White et al. 2011). However, since our results still show important sensitivity to precipitation, soil moisture modelling within the CERES-Maize model needs to be improved. Additionally, a recent study found that models such as CERES-Maize that use the Priestley-Taylor method to simulate ET do not incorporate the effects of vapour pressure deficit (VPD) on potential transpiration, and thus affect ET and water stress calculations, and may underestimate crop response to higher temperatures (Lobell et al. 2013). These deficiencies in the soil-plant-atmosphere module of DSSAT need to be addressed in order to reduce uncertainties.

The two main processes in crop growth models (radiation interception and photosynthesis) require detailed spatial and temporal weather-related data (Van Bussel et al. 2011). However, such information is often not available, especially when working at a larger scale. This may limit the performance of these models (Bert et al. 2007). Additionally, the spatiotemporal aggregation of such data may reduce the non-linear and dynamic relations between weather, management, soils, nutrients, and cultivar (Van Bussel et al. 2011). Finally, the way these processes are modelled is key since they may yield different results (Adam et al. 2011). Thus, the scale of analysis, the availability and quality of data, and details of the modelling approach may influence outcomes in crop model simulations.

Policy makers may also be concerned about the accuracy of future crop yield estimates since many of the most frequently used models do not take into ac-count the damage caused by extreme heat, insects or floods, or account for changes in the broader watershed (Tubiello et al. 2007; Challinor and Wheeler 2008; Lobell et al. 2009). These are events that are rather frequent but quite poorly modelled by most process-based (White et al. 2011; Maltais-Landry and Lobell 2012) and statistical models (Soussana et al. 2010). Some studies, using high quality spatial and temporal data showed that temperatures above a certain threshold during key stages of crop growth may have considerable effects on yields. Thus, these effects need to be incorporated in crop models to better estimate crop responses to changes in climate. Additionally, there is a debate on the usefulness of these highly calibrated process-based models, on the one hand, and statistical models, on the other, which are restricted to current climates and at-mospheric conditions while not taking into account genotype, management, CO_2 and other environmental factors. While there is a general consensus now that we need to follow a multi-model approach in analysing the climate impacts on crop yields, much work is still needed to improve the individual models. Whether using a process-based model or statistical methods, the scale of the analysis, the quality of the data used, and other model limitations influencing crop yields need to be taken into account. Reducing the uncertainties linked to these factors will help policy makers who, under budgetary pressure, need to make decisions on well-targeted and high-impact adaptation measures aimed at reducing the potentially devastating impacts of climate change on agricultural production.

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Chapter 10
Development of a Prioritization Tool for Climate Change Adaptation Measures in the Forestry Sector—A Nicaraguan Case Study

Tania Guillén Bolaños, María Máñez Costa and Udo Nehren

10.1 Introduction

As part of the natural system, forests are impacted by climate change. At the same time, they are also important CO_2 sinks. As stated in the 5th Assessment Report of the IPCC, all natural (including forests) and human systems will need to adapt as it "will be necessary to address impacts resulting from climate change that is already unavoidable due to past emissions" (Mimura et al. 2014, p. 873). But until recent years, adaptation has been seen as "an unnecessary luxury rather than as an integral part of development policy" (Chambwera 2010, p. 29).

This situation has been also identified for the forestry sector, specially in developing countries, where the adaptation potential to contribute in decreasing the vulnerability of rural areas is high, however vastly underexploited.

In recent years, adaptation has gained more attention and has been enhanced by the Cancun Agreements which state that "adaptation must be addressed with the same priority as mitigation and requires appropriate institutional arrangements to enhance adaptation action and support" (UNFCCC 2011, p. 3). This guideline has been reinforced by the Paris Agreement, approved by the parties under the UNFCCC at the COP 21.

Countries face different challenges during the planning process for climate change adaptation projects. One of the main challenges highlighted by the IPCC (IPCC 2007), is the lack of tools which help prioritize among available adaptation measures, especially when financial resources are limited.

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This study contributes to closing the existing knowledge gap by presenting a tool which has been developed for the prioritization of climate change adaptation measures in the forestry sector. A biosphere reserve in Nicaragua is used as an empirical basis. Nicaragua serves the demands of an empirical example for the following reasons: as the developing country with the largest forest resources in Central America and highly vulnerable to the effects of climate change. With respect to habitat change, the climate-related changes put Nicaragua among the most vulnerable countries, ranking its vulnerabilities from acute to severe (DARA 2012).

10.2 Bosawas Biosphere Reserve

Bosawas Biosphere Reserve, located in the north of Nicaragua, is the largest non-intervened protected area in Central America (Buss 2011). It has 3.5% of the world's biodiversity within its territories, active presence of indigenous communities, and represents an important provision of environmental services and products (MARENA-SETAB-GTZ 2009).

When the study was realized, there was no specific information related to the different climatic scenarios for the end of the century for Bosawas. However, the Humboldt Center, the National Institute of Territorial Studies (INETER), and the Meteorological Institute in Cuba (INSMET) developed an experiment related to the sensitivity of the life zones classification of Holdridge in the area. The experiment was realized for the period 2012–2035, using eight climatic variables, a resolution of 25×25 m, a moderate scenario, and the PRECIS Q4 model. In order to present the changes of the life zones, six different periods are used.

Figure 10.1 shows the results of the experiment, where a drastic change of Bosawas ecosystems can be clearly observed. From the humid forest in year 2012, a change of approximately 70% to dry tropical forest by year 2035 is projected, where most of the change occurs between the last two periods. Those results match the projected impacts identified by CEPAL (2010) and IPCC (2007), which observe significant increases in temperatures and changes in rainfall patterns by year 2030.

Considering this potential scenario, it is clear that the implementation of measures in order to adapt to the projected changes is essential for the Nicaraguan forestry sector, especially in Bosawas. Considering the limited financial resources, the prioritization of the potential measures to be implemented becomes a core step in the planning process.

10.3 Planning for Climate Change Adaptation

Due to the different and multiple levels and dimensions of climate change, adaptation to this phenomenon is a complex process. Therefore, to determine which alternative is better to be implemented with a limited budget, capacities, etc., a selection and

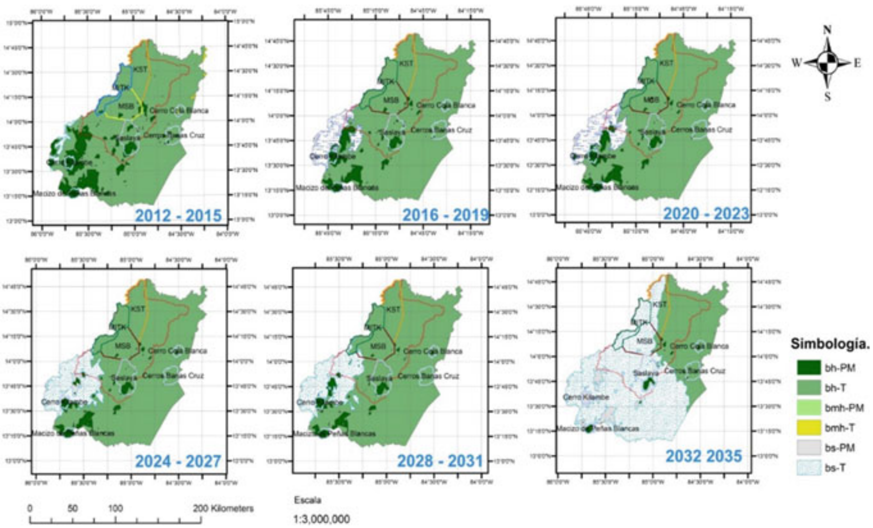

Fig. 10.1 Sensitivity of Holdridge life zones to climate change in Bosawas. *Source* Centro Alexander von Humboldt (2013)

prioritization process is a key step concerning adaptation planning (Noble et al. 2014).

Related to the formulation and implementation process of national adaptation plans, the UNFCCC (2015) identifies the prioritization of climate change adaptation as part of implementation strategies.

Considering that decision making is done under uncertainty, two types of tools have been identified to inform the process: top-down and bottom up tools. The first one refers mostly to downscaling of simulated climate scenarios; the second is driven by the different stakeholders who identify their own impacts and vulnerabilities and incorporate adaptive options for the appropriate sector or community. However, noting the challenges and complexity of adaptation, it is clear that “no single tool suits all circumstances” (Mimura et al. 2014, p. 883). Nowadays this is one of the biggest challenges that governments, practitioners and communities still face around the world when considering adaptation to climate change (IPCC 2007).

Noble et al. (2014, p. 850) identify some aspects that have to be considered when selecting adaptation options, amongst them:

- Effectiveness in reducing vulnerability and increasing resilience
- Efficiency (increase benefits and reduce costs)
- Stakeholder participation, engagement and support
- Legitimacy and social acceptability
- Designed for an appropriate scope and time frame
- Resources available

10.4 Conceptual Framework for the Prioritization of Adaptation Measures

Considering the aspects identified as important by Noble et al. (2014), the development of the tool for the prioritization of adaptation measures, in line with the general objective of this study, is conceptualized around the development path (Fig. 10.2) for a prioritization tool, presented in Máñez and Cerdá (2014) considering the IPCC guidelines (Carter et al. 1994).

The structure comprises seven steps. The first three include the description of the area under study (Step 1), respective climate change scenarios (Step 2) and their impacts on the sector of interest (Step 3). All these steps are based on information collection. Part of the information related to these three steps is presented in Sect. 10.6 as part of the case study area description.

The next steps represent the core of this work and are those related to, and developed according to, the specific objectives of this research. Here, the development concept makes use of the Analytical Hierarchy Process (AHP), being a MCA method: identification of adaptation measures (Step 4), definition of criteria for analysis (Step 5), prioritization of adaptation measures (Step 6) and results and analysis according to the developed prioritization tool (Step 7). In the last step (7), the measures to be implemented are chosen, using the outcome of the prioritization tool as a guideline for decision-making. Steps four to seven are presented in Sect. 10.6 of this piece of work. In the following, a description of the method for prioritization and the approaches used for the development of this study are given.

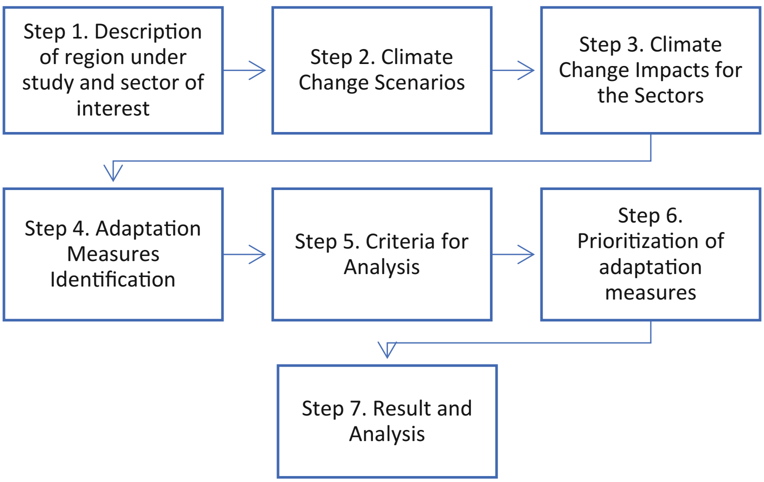

Fig. 10.2 The concept: General structure of a prioritization tool. *Source* Máñez and Cerdá (2014)

10.4.1 Methods for Prioritization: Multi-Criteria Analysis (MCA)

The Multi-Criteria Analysis (MCA) is described as "any structured approach used to determine overall preferences among alternative options, where the options accomplish several objectives" (UNFCCC Secretariat 2005). Thus, the term MCA encompasses several methods of its kind. The methods are classified as those, which give clear recommendations for actions by comparing and ranking different outcomes or alternatives (UNEP 2011; Heuson et al. 2012). It has been used for the evaluation of climate change policies (De Bruin et al. 2009), by the scientific community as well as by practitioners in the field of adaptation (Ishizaka and Labib 2011).

To prioritize climate change adaptation measures, different dimensions, such as the technical, financial, social and environmental feasibility must be considered (CARE 2010). Therefore, the inclusion of a great number of climate change dimensions in a MCA method ensures transparency and accountability (UNEP 2011). The MCA methods can be used when monetary values cannot be assigned to significant environmental and social impacts. Instead, MCA uses attributes or indicators; these do not have to be defined in monetary terms, but are often based on a quantitative analysis (UNFCCC Secretariat 2005; Nasra et al. 2010; UNEP 2011; Heuson et al. 2012).

Compared with cost-benefits analysis, MCA tools can lead to more complete assessments, as well as minimizing the chances of making mistakes that lead to maladaptive assessment. This is due to MCA including more than just the economic advantage of the options (Magrin 2015).

Another advantage of the MCA method is its participative character, where different stakeholders, experts and/or practitioners—with different knowledge, experience, and backgrounds- can participate in the weighting process (Nasra et al. 2010), which is very important when addressing the challenges of climate adaptation (Noble et al. 2014).

The main critics regarding MCA are related to the role of judgment during the process, which can be subjective (UNDP 2004; Saaty 2008). Through the use of MCA methods, quantitative results and their reproducibility can be obtained (Nasra et al. 2010). The authors consider that these two aspects are important for the development of an effective prioritization tool.

10.4.2 Analytic Hierarchy Process as a Multi-Criteria Analysis

Among the multi-criteria decision-making tools, the Analytic Hierarchy Process (AHP), developed by Saaty (1980, 2008), has proven to be useful for different sectors and objectives (e.g. selection, evaluation, decision-making, benefit and cost analysis, etc.) (Vaidya and Kumar 2006). This method is based on weighting and has been

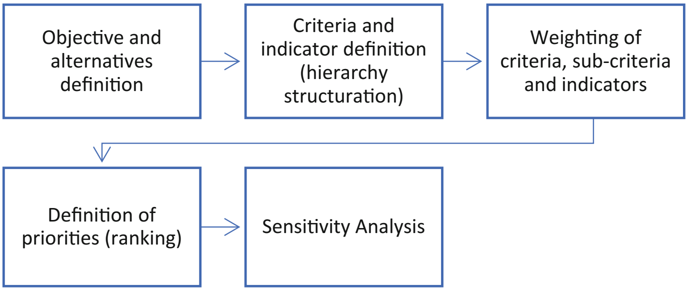

Fig. 10.3 MCA steps. *Source* Own elaboration based on Carter et al. (1994); Greening and Bernow (2004); Saaty (2008); Nasra et al. (2010); Nairobi Work Programme-UNFCCC (2011)

extensively used for environmental issues (Greening and Bernow 2004; Ishizaka and Labib 2011). The weighting process is performed by pairwise comparison matrices, among criteria, sub-criteria and indicators. Mendoza and Prabhu (2000) mention that, compared with the ranking and rating methods, the AHP is the one which provides more information when evaluating different indicators.

The general steps of a MCA using AHP are presented in Fig. 10.3.

10.5 Prioritization Tool for Climate Change Adaptation in the Forestry Sector

The development of the prioritization tool is achieved by the application of the development path introduced in Fig. 10.2, to the case of the forestry sector in Nicaragua, focusing on steps four to seven, namely the identification of adaptation measures, the definition of criteria for analysis and the prioritization of the measures, following the steps presented in Fig. 10.3.

As previously mentioned, for the development of the climate change adaptation prioritization tool, the authors used a MCA, using the Analytic Hierarchy Process (AHP) developed by Saaty (1990, 2008). The decision was made based on the advantage of being able to have a participative instrument, which allows including non-monetary aspects in the decision-making for climate change adaptation in the forestry sector. Also, the AHP, compared with other MCA methods, gives clear recommendations to those that need to make the decisions regarding implementation of adaptation options.

Regarding the identification of potential adaptation measures, since adaptation in natural ecosystems is "an autonomous process", it is difficult to identify measures, which exclusively work for adaptation. Therefore, the authors also consider measures which make use of the synergy between mitigation and adaptation to climate change as well as approaches that can be related to resource management, such as agroforestry systems and watershed management approaches, which have a direct or indirect impact on the forestry sector. Three different measures, already implemented in the country were identified and selected.

For the creation of the list of criteria, sub-criteria and indicators, which allows for the evaluation of each measure, the authors considered the definitions proposed by CIFOR (1999, p. 9). Criteria and sub-criteria are defined as "the intermediate points to which the information provided by the indicators can be integrated and where an interpretable assessment crystallizes". The criteria can be categorized as part of different components on different levels. Indicators are defined as "any variable or component of the forest ecosystem or management system used to infer the status of a particular criterion". For the weighting of the criteria, the authors decided to consider the weights presented in Mendoza and Prabhu (2000) and the suggestions made by governmental and non-governmental representatives during the information gathering process.

As a result, the proposed tool is comprised by four different hierarchical levels, being: alternatives or measures to be evaluated (level 4) through the use of 26 indicators (level 3) is proposed. The indicators are comprised within 11 sub-criteria (level 2) and 6 different criteria (level 1), which are grouped in the only objective of prioritization of the adaptation measures in a hierarchical structure (Fig. 10.4).

10.6 Prioritizing Adaptation Measures in Bosawas

As mentioned before, three different adaptation measures were identified to be evaluated for Bosawas. Due to the lack of detailed information regarding adaptation measures already implemented or those in the planning and implementation phase in the case study area, the identification (of measures) had to rely on information coming from measures that are part of projects that were already implemented by the Government of Nicaragua in other areas of the country, which were also considered as part of the Plan for Protection and Management of Bosawas (MARENA 2012). The identified adaptation measures are:

1. Rehabilitation of ecosystems through the establishment of agroforestry systems
2. Conservation, reforestation and natural regeneration
3. Establishment of forestry management systems

After identifying the measures, the prioritization is realized by making use of the hierarchical representation of criteria, sub-criteria and indicators as shown in Fig. 10.4. Each criterion, sub-criterion and indicator are assigned different weights according to their importance in achieving meaningful adaptation outcomes when fulfilled by a measure.

The weights of levels 2 and 3 are defined by the AHP process (pairwise comparison), while for level 1, the weights are defined based on literature and suggestions collected from interviews with Nicaraguan officers. Therefore, for level 1 the weights are distributed as following: 26% to environment and climate-related, 7% to

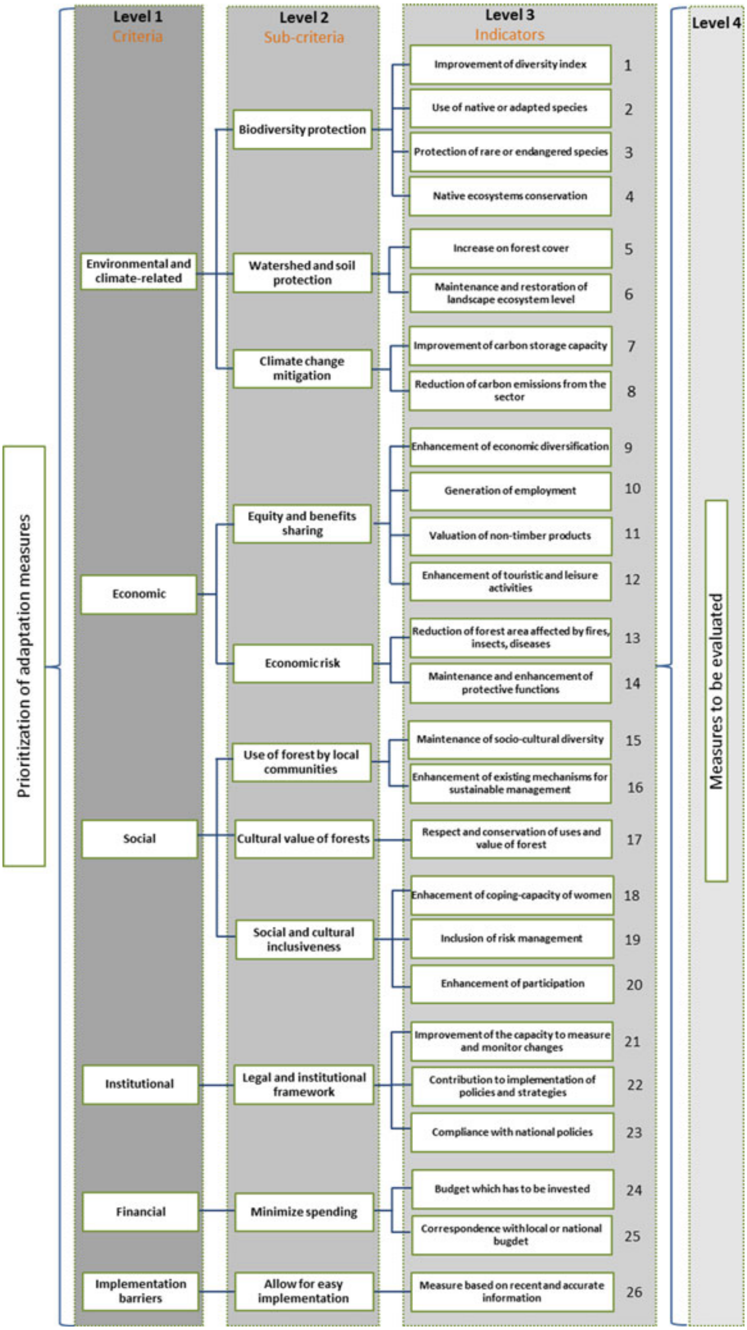

Fig. 10.4 Hierarchical representation of defined criteria and sub-criteria for a prioritization tool for climate change adaptation in the forestry sector. *Source* Own elaboration, based on UNEP (2011)

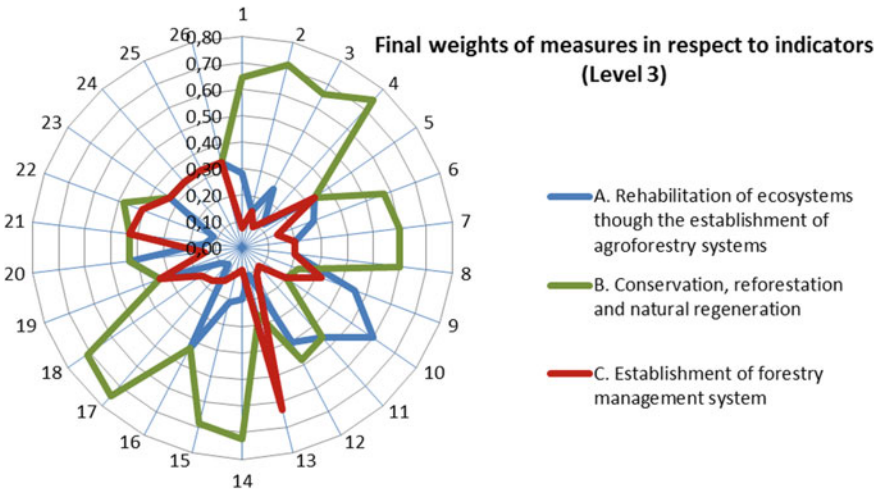

Fig. 10.5 Final weights of measures in respect to indicators

economic, 20% to social, 12% to institutional, 20% to financing needs, and 15% to implementation barriers.

Once the weights are defined for the different levels of the tool, the prioritization itself is then realized by assessing each measure's performance against each of the 26 indicators listed in the hierarchical representation of the prioritization tool (Fig. 10.4). Then, all possible pais of assessed measures are compared for each indicator. Using this pairwise comparion allows for a prioritization of measures according to their contribution to adaptation.

Figure 10.5 presents a radar graph which allows for the observation of the performance of every measure, relative to each of the 26 proposed indicators, based on author's judgement. There, it can be easily observed that measure B is the one that performs best with respect to most of the indicators. Measure C shows a good performance related to most of the economic indicators. Measure A shows a good performance, but it does less so regarding environmental and climate-related indicators, where measure B performs better. Hence, it can be affirmed that an adaptation measure fulfilling certain criteria or indicators, while performing only modestly on others can still be given priority for implementation.

Table 10.1 and Fig. 10.6 present the results of the prioritization process of the selected adaptation measures, using the weights of the defined criteria, sub-criteria and indicators, as presented in the developed prioritization tool.

According to the results, the "conservation, reforestation and natural regeneration" measure (measure B) is the one with the highest weight (46%), followed by the "establishment of forestry management systems" (28%), then the "rehabilitation of ecosystems through the establishment of agroforestry systems (26%).

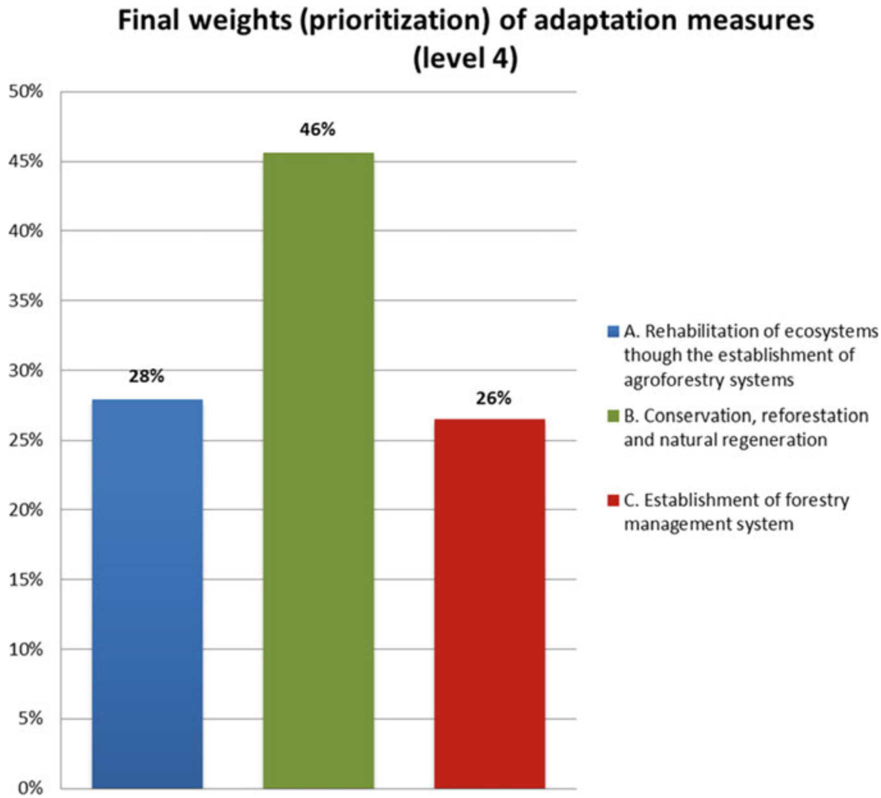

Fig. 10.6 Final weights (prioritization) of adaptation measures

Table 10.1 Ranking of priorities of adaptation measures according to weights

Adaptation measure		Weight	Ranking
B	Conservation, reforestation and natural regeneration	0.46 (46%)	1
A	Rehabilitation of ecosystems though the establishment of agroforestry systems	0.26 (26%)	3
C	Establishment of forestry management system	0.28 (28%)	2

Therefore, the ranking of priorities of the measures considering the different defined criteria, sub-criteria and indicators for the forestry sector in the case study area are presented in Table 10.1:

10.7 Conclusions

The Nicaraguan forestry sector was chosen as the case study, which helped the development of the prioritization tool for climate change adaptation measures based on the characteristics of this sector. The tool comprises important aspects mentioned by government representatives and literature as being essential for planning tools: the inclusion of social, economic and environmental aspects.

The proposed tool for prioritization of adaptation measures fulfilled the general objective proposed for this work. The proposed tool follows the general steps included in the guidelines for evaluation of the impacts of climate change, vulnerability and evaluation of adaptation measures. In addition to the guidelines however, the tool presents a specific methodology to prioritize in a transparent way. It also offers a possibility to take the opinions of experts, practitioners and/or stakeholders related to the sector under study into consideration. Even though the results of this work reflect the author's judgment, it is considered to be empirically relevant.

It can be confirmed that the prioritization tool is flexible as its structure allows for adaptations considering different contexts. The adjustment of the tool for prioritization of measures for other sectors is also possible. These adjustments could affect the calculated weights presented in this work; therefore, new calculations would have to be carried out. However, the calculations don't represent a high level of complexity. Therefore, the tool is also transferable.

The methodology may present difficulties during the calculation of the weights due to the different hierarchical levels, but the authors consider a short training would be sufficient to transfer the knowledge. Another characteristic of the proposed tool is that it can be complemented by tools or methods more specific to different aspects, such as cost-benefit or cost-efficiency analysis for the financial aspect.

The tool is reliable if the results are obtained based on the judgment of experts, practitioners, and even stakeholders, which may also generate greater acceptance of the final results. The consistency of the judgement can also be confirmed through the sensitivity analysis. This characteristic also fits with those mentioned by government representatives.

For the case study area, the "conservation, reforestation and natural regeneration" measure was ranked as number one for its implementation. This measure is more related to the conservation and preservation of natural ecosystems, which in the case study area are associated to indigenous communities who have forest and land ownership. The measure showed to perform best regarding environmental and climate-related, socio-cultural, and institutional aspects. The selection of this alternative as the prioritized measure confirms Ohlson et al. (2005), who, concerning adaptation in natural ecosystems, claim autonomous responses to be the most appropriate adaptation measures.

More specific and detailed information regarding climatic scenarios is needed to assess the impacts on the forestry sector of Nicaragua for different scenarios, as intended at the outset of this work.

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