A contribution to the study of the economic causes and consequences of climate change:

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10 A methodology for the risk assessment of climate variability and change under uncertainty. A case study: coffee production in Veracruz, Mexico

Existing methods for the assessment of the potential impacts of climate change in productive activities and sectors are usually limited to point estimates that do not consider the inherent variability and uncertainty of climatic and socioeconomic variables. This is a major drawback given that only a limited and potentially misleading estimation of risk can be expected when ignoring such determinant factors.

In this chapter, a new methodology is introduced that is capable of integrating the agent's beliefs and expert judgment into the assessment of the potential impacts of climate change in a quantitative manner by means of an objective procedure. The goal is to produce tailor-made information to assist decision-making under uncertainty in a way that is consistent with the current state of knowledge and the available subjective "expert" information. Time-charts of the evolution of different risk measures, that can be relevant for assisting decision-making and planning, can be constructed using this new methodology.

A case study of coffee production in Mexico is used as an illustration. Time-dependent probabilistic scenarios for coffee production and income, conditional on the agent's beliefs and expert judgment, are developed for the average producer under uncertain future conditions. It is shown that variability in production and income, generated by introducing climate variability and uncertainty are important factors affecting decision making and the assessment of economic viability that are frequently ignored. The concept of Value at Risk, commonly applied in financial risk management, is introduced as a

This chapter is based on Estrada F, Gay C, Conde C (2012) A methodology for the risk assessment of climate variability and change under uncertainty. A case study: coffee production in Veracruz, Mexico. Clim Change 113(2), 455-479. DOI 10.1007/s10584-011-0353-9 means for estimating the maximum expected loss for a previously chosen confidence level. Results are tailor-made for agents that have incomplete information and different beliefs. The costs of climate change for coffee production in Veracruz are estimated to have a present value representing from 3 to 14 times the current annual value of coffee production in the state.

10.1 Introduction

Since the late 1990s important advances have taken place in the development of methodologies for estimating the potential impacts of climate change on human and natural systems. The standard approach of climate scenario-driven impact studies has been extended to a range of different approaches such as the assessment of current and future adaptation capacity, social vulnerability and policy, among others (Carter et al, 2007).

The Fourth Assessment Report (AR4, IPCC-WGII, 2007; Carter, et al., 2007) briefly reviews the new assessment methods for climate change impact, adaptation and vulnerability (CCIAV). The IPCC distinguishes five approaches for CCIAV, four of them are considered conventional: impact assessment, adaptation assessment, vulnerability assessment and, integrated assessment. The fifth approach, risk management, has evolved as the CCIAV studies have begun to be used in mainstream policy-making (Carter et al., 2007). These studies are oriented towards decision-making activities such as planning, management and policy-making, and are suitable for a wide range of scales: from global to local and from sector to case study.

The development of models that combine physical and socioeconomic determinants has also been of particular importance since it has allowed the integrated assessment of potential impacts, providing more realistic estimates that consider multiple stressors. Nevertheless, some other issues like uncertainty and variability are still pervasive in CCIAV studies, and there is a lack of methodologies to formally address them. For example, even in the UNFCCC's *Compendium on methods and tools to evaluate impacts* *of, and vulnerability to, climate change* (UNFCCC, 2008a) there are few methods that integrate uncertainty and variability in their estimates.

Most of the current assessments of the potential impacts of climate change have been carried out using methodologies that do not allow the inclusion of the variability and uncertainty inherent to climate and socioeconomic variables. In consequence, such methodologies can only provide a very limited (and potentially biased) assessment of the risk that the systems in study would face under climate change conditions, given that they are based on a single realization of a combination of different stochastic processes.

In the AR4, the Working Group II of the IPCC stresses the importance of producing new methods to address uncertainty in climate change studies in order to inform decision-making under uncertainty, and provides examples of studies that have suggested methods to do this (see for example, Toth et al., 2003a; Toth et al., 2003b; Jones, 2001; Willows and Connell, 2003; UNDP, 2005; more recent studies include, for example, Tebaldi and Lobell, 2008).

The methodology proposed in this paper builds on the risk management framework and aims to inform decision-making under uncertainty by producing probabilistic assessments of the potential impacts of climate change that: consider the uncertainty in climate and socioeconomic variables as well as their inherent variability; promote stakeholder involvement by including their subjective information and; produce tailor-made risk measures as well as estimates of the date to reach critical thresholds defined by the stakeholder.

10.1.1 Uncertainty in climate scenarios

In recent years, advances in the understanding and modeling of the climate system have permitted to increase the confidence in, and the complexity of, climate models as well as to further improve the space and time resolution of climate change scenarios (IPCC-WGI, 2007). There is now the possibility of estimating uncertainty ranges for the future climate at global and regional levels and of constructing probabilistic climate change scenarios using different storylines and models (Meehl et al., 2007a; Christensen et al., 2007a).

Unfortunately, due to the lack of appropriate methodologies for handling uncertainty in climate change scenarios, a large portion of the available information is being poorly exploited for CCIAV and therefore, climate change science is failing to fully accomplish one of its main objectives: assisting decision-making and promoting optimal or "best response" decision-making.

The vast majority of the literature on impact assessment is based on recommendations such as using at least two climate change scenarios (the highest and lowest or those corresponding to two development scenarios that, based on "expert" subjective information, are thought to be most likely) for addressing uncertainty in climate projections (UNFCCC, 2008a,b). This is one of the most common recommendations that have been used in large-scale assessments such as National Communications (e.g., Gobierno de la República de Argentina, 2008; Secretaría de Medio Ambiente y Recursos Naturales/Instituto Nacional de Ecología, 2006; Government of Japan, 2006; Government of the Federal Republic of Germany, 2006). Nevertheless, results following these recommendations are usually hard to interpret, provide no measure of the probability of the different outcomes, are difficult for communicating risk to stakeholders and decision-makers, and do not make full use of the available information/uncertainty.

Since over a decade, new methodologies for impact assessment that are more suitable for dealing with uncertainty have been developed and implemented (see for example, Titus and Narayan 1996; Yohe and Schlesinger 1998; Jones 2000; New and Hulme 2000; Preston 2006; Nawaz and Adeloye 2006; Gay et al. 2006c). These methodologies can take advantage of the recently available possibility of constructing probabilistic climate change scenarios but greatly depend on the assumptions needed to express uncertainty in terms of a probability distribution. One of the major pitfalls is that these probability distributions are commonly presented as "objective" facts because they are based on a frequentist approach, when it should be clearly stated that they are all subjective representations of beliefs (Moss and Schneider, 2000; Ahmad and Warrick, 2001; Gay and Estrada, 2010). Subjective beliefs should be brought forward, be clearly stated, and probability distributions should be a meaningful expression of the decision-maker beliefs and not some impersonal, one-size fits all, statistically inadequate device.

Dealing with uncertainty in climate change scenarios has become an issue of intense debate in the scientific community (Schneider, 2001, 2002; Allen, 2003; Grüber and Nakicenovic, 2001; AR4-WGI, 2007; for example) that has led to the proposal of different methods. The contribution of the Working Group I (WGI) to the IPCC's AR4 provides a review of some of the advances that have taken place in the last decade regarding probabilistic scenarios and uncertainty management.

In the AR4, the WGI takes on the issue of trying to assess model uncertainty and provides *best estimates* or multi-model averages, *likely ranges*, as well as other types of probabilistic scenarios for the six marker scenarios included in the Special Report on Emissions Scenarios (SRES, Nakicenovic et al., 2000). Some of the shortcomings of the approaches included in the WGI contribution to the AR4 for producing probabilistic climate change scenarios have been discussed by the authors in a previous paper (Gay and Estrada, 2010). We believe that one of the basic problems is that, in general, the approaches proposed are based on *forecast* methodologies. These methodologies are designed to address aleatory uncertainty and not epistemic uncertainty, which is dominant in climate change scenarios. In this manner, forecast methodologies cannot handle epistemic uncertainty and therefore they may not be adequate for supporting decision-making.

Furthermore, the IPCC keeps avoiding the emissions uncertainty and therefore, these probabilistic scenarios are conditional on the emission scenario for which we have no information regarding its probability of occurrence. Consequently, decision-makers are left again without probability estimates which are conditional on something for which probabilities of occurrence have not be assigned, to carry on with their responsibilities.

Other methods that have become popular are based on weighting models accordingly to their accuracy reproducing observed climate (see for example, IPCC-TGICA, 1999, 2007; Wigley, 2008, Carter et al., 2007). This type of methods might provide important information which might be used to reduce uncertainty. Nevertheless, there is no guarantee that the models that provide an accurate representation of the current climate will continue to do so in the future, and therefore this method could lead to trading uncertainty by ignorance (Schneider, 2003). Also, the diversity of models could be at stake, and models could become less and less independent (Allen, 2003).

All these methodologies represent important advances towards making climate change science increasingly useful for decision-making. Nevertheless, all of them still greatly dismiss uncertainty and therefore do not provide an adequate representation of the current state of knowledge in climate modeling. It is important to realize that the complexity of the problem ensures that the available information for decision-making will always be incomplete and that therefore scientific or objective information will have to be complemented with subjective expert information. As discussed by the authors in a previous paper (Gay and Estrada, 2010), objective probabilities in climate change scenarios are not attainable and therefore no “true or objective” impact scenario can be constructed, even in a probabilistic framework.

This paper uses the methodology for constructing probabilistic climate change scenarios proposed in Gay and Estrada (2010) and based on the Maximum Entropy Principle. These estimates have desirable properties such as: they are the least biased estimate possible on the available information; maximize the uncertainty (entropy) subject to the partial information that is given; the maximum entropy distribution assigns a positive probability to every event that is not excluded by the given information; no quantifiable possibility is ignored. The probabilities obtained in this manner are the best predictions possible with the state of knowledge and subjective information that is available.

10.1.2 Natural climate variability

Estimates about how climate variability could evolve under climate change conditions are commonly based on simulations from physical climate models (e.g., General Circulation Models). The two main approaches are based on performing basic statistical analysis on one single run or on ensembles of runs of the same climate model.

For example, the document Handling Uncertainties of UK Climate Impacts Programme[37] recommends estimating future climate variability by creating an ensemble of three simulations of the same model under the same emissions scenario and parameterizations but with slightly different initial conditions. The variability shown by these simulations is assumed to adequately represent natural climate variability under a particular climate change scenario. On the other hand, the MAGICC-SCENGEN software (developed by the Climate Research Unit and the National Center for Atmospheric Research, Wigley, 1994, 2003, 2008; Hulme et al., 2000), which is widely used for investigating future climate change at global and regional levels, uses 20-year samples for calculating the standard deviations of single simulations for approximating future climate variability (Wigley, 1994, 2008).

Both approaches have important drawbacks. On the one hand, although the ability of climate models for simulating the climate system at global and regional scales has greatly improved, climate models are currently not able to entirely reproduce observed climate variability (Meehl et al., 2007b; Christensen et al., 2007a). In addition, using a limited number of model runs (three, for example) will hardly produce an adequate representation of even the *model's internal variability*, much less will it provide an approximation of present, and even worse, of future natural climate variability.

On the other hand, using fixed sample sizes (20 years in the case of the MAGICC-SCENGEN software) of climate model simulations —or for that matter, observed sub-samples of 30 years (WMO, 1983)— for estimating climate variability will clearly

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[37] http://www.ukcip.org.uk/scenarios/ukcip02/documentation/handling_uncertainty.asp

produce deficient estimates. There are two main reasons for this argument: first, by definition, under climate change, climate variables will be (are) non-stationary processes, so if the time-series properties of these processes are not considered for any statistical analysis (even for calculating a simple standard deviation), they are very likely to lead us to find spurious changes in the moments of their distribution (Gay et al., 2007). In this case, climate variability could be wrongly thought to be time-dependent and therefore could be expected to increase (decrease) in the future, producing poor estimates of potential future climate risk. In this case, limiting sample size to 20, 30 or to any fixed number or years will still produce inadequate estimates of climate variability. Second, if the process turns out to be stationary, limiting the sample size to a sub-sample of the available data will only produce inefficient estimates of its variability.

Recent studies (Gay et al., 2007; Gay et al., 2009; Estrada et al. 2010; IPCC-WGI, 2007) suggest that climate change will possibly manifest as a change-in-the-mean of (some) climate variables, without altering other distribution moments, at least in the case of monthly and annual means.

For these reasons, it is proposed that the best estimation of future climate variability is the best possible estimation of current natural variability, given that it also provides information of how climate variables have responded to current observed climate change. For this purpose, this chapter uses statistically adequate time-series models[38] to infer the corresponding *data generating processes*.

10.2 Methodology description and simulation procedures

The simulation methodology presented here considers two possible alternatives for generating probabilistic scenarios of the potential impacts: a) static, which generates a potential impact distribution for a particular time horizon (e.g., 2020 or 2050) and; b)

[38] A statistically adequate model satisfies its probabilistic assumptions. As such, a it ensures "the empirical validity of the probabilistic assumptions underlying a statistical model" (Spanos and Mcguirk, 2002; Andreou and Spanos, 2003). Statistical adequacy provides a sufficient condition for statistical inference because it presupposes the validity of the model specification assumptions (Andreou and Spanos, 2003).

dynamic, which provides the evolution of the potential impacts' distribution over a time period (e.g., present time to 2050). The methodology for both alternatives can be described in the following steps:

1) Define potential input and output variables for model and simulation.

2) Build a statistically adequate model for the dependent variable being simulated. This simulation methodology could also be applied to other types of models such as physically based crops simulators, water-balance models or any other type of model that can be adapted for producing a large number of simulations.

3) Obtain a comprehensive range of climate change scenarios for each of the climate variables used as input variables for simulation. Obtain, as well, future scenarios for the non-climate variables included as input variables.

4) Obtain the maximum entropy distributions for climate and non-climate variables. For this step, it is required to choose an arbitrarily mean average change. As described in Gay and Estrada (2010), two main approaches can be used for selecting this arbitrary average value:

a) The first approach makes use of the agent's attitude towards uncertainty (see, for example, Mukerji, 2000; Kelsey and Eichberger, 2009; Stein and Segal, 2006; Wakker, 2001). When decisions are to be taken under subjective, deep or epistemic uncertainty, the decision-maker has limited knowledge or information to assign probabilities to the various possible outcomes. As stated by Ellsberg (1961) "what is at issue might be called the ambiguity of this information, a quality depending on the amount, type, reliability and "unanimity" of information, and giving rise to one's degree of "confidence" in an estimate of relative likelihoods" [39]. In this case an *uncertainty averse or ambiguity averse* decision maker adjusts his probability distribution on the side of caution in response to his imprecise knowledge of the odds (Mukerji, 2000). In Gay

[39] Ellsberg (1961) distinguishes between situations when the decision-maker: 1) lacks of any information whatsoever ("complete ignorance") in which rules such as minimaxing, maximaxing, Hurwicz criteria or minimaxing regret are adequate; 2) has enough information to assign a definite and precise probability distribution. In this case the "Savage axioms, and the general "Bayesian" approach, are unquestionably appropriate ... his uncertainty in such a situation is unequivocally in the form of "risk"." and; 3) a state of information in which the problem cannot be characterized as ignorance or risk and falls in what is called "Knightian", deep or epistemic uncertainty. This is when *ambiguity* arises, and we believe that this is the case of probabilistic climate change scenarios.

and Estrada (2010) three types of attitudes towards uncertainty are used: cautious, neutral and reckless. The term cautious agent is used for those agents that when facing an uncertain situation will assign a higher subjective probability of occurrence to the least favorable outcomes than a neutral agent would. This type of decision-maker will chose a higher average mean change than the central value of the distribution (defined as the sum of the lowest and highest values divided by two). A neutral decision-maker would choose a uniform distribution which is a maximum entropy distribution in the absence of additional information; his attitude towards uncertainty does not lead him to assign higher or lower weights to any possible outcome. In such manner he will chose the central value of the distribution as the average mean change. A reckless decision-maker will tend to select a lower average mean change than the central value of the distribution, assigning lower probability of occurrence to the least favorable outcomes, showing a lower level of concern for the possibility of underestimating the probabilities of occurrence of these outcomes.

b) The second approach consists in choosing "high" and "low" average change values, as is currently recommended for other methodologies used for impact assessment. The relative entropy and the information index can be used to keep track of how much the probability assignment depends on the included subjective information.

5) Build statistically adequate time-series models in order to infer the properties of the data generating processes of the input variables. With this information, produce stationary time-series of these variables and find the probability distribution that provides the best fit. Possible correlation among input variables should be taken into account[40]. For other input variables for which information is not available or is judged to be non-representative of their future evolution, choose non-informative probability distributions such as uniform, for example. Uniform distribution is a maximum entropy distribution when no additional information is available.

6) a) If the objective is to generate a realization for a given time slice (e.g., 2050) proceed as follows. Generate a random number from one of the maximum entropy distributions in step 4, and use it as the mean of the corresponding probability distribution

[40] If the input variables are correlated, MCMC simulation can be employed in order to capture the variables dependence. If variables are normally distributed, Cholesky decomposition can also be applied.

found in step 5. Generate a realization form this distribution. Repeat for each variable. b) If the objective is to generate a dynamic simulation for a time period of length *n* such that *t=1, 2,…,n*, proceed as follows. Generate a realization from the maximum entropy distribution and divide it by *n* (the length of the time period). This will be the slope of a linear trend of length *n*. Generate random numbers from the probability distribution in step 5; generate a realization of size *n* of the data generating process (white noise, autoregressive (AR), moving averages (MA), ARMA, etc.) and add it to the linear trend. Repeat for every explanatory variable.

7) Define the evolution of the uncertainty for variables represented with non-informative distributions. For example, it could be reasonable to represent our increasing uncertainty regarding the value that a price could take in the future by means of a uniform distribution with a time-dependent support. Repeat for every variable for which information is not available or is judged to be non-representative of their future evolution.

8) Introduce these simulations as input variables in the model defined in step 2. Save the realizations of the desired output variables.

9) Repeat steps 6, 7 and 8 in order to obtain the desired number of simulations.

This methodology offers the advantage of integrating the user's beliefs and expert judgment in the probabilistic assessment of the potential impacts of climate change in a quantitative way. In this manner, tailor-made information is obtained for the decision-maker and opens the possibility of offering time-dependent information for decision-making concerning the potential impacts of climate variability and change that is consistent with the current state of knowledge and the subjective "expert" information available. Producing time-dependent information is crucial for planning, policy making and for building possible adaptation strategies.

10.3 Methodology illustration: a case study of coffee production in Veracruz, México.

In this section, a simple illustration of this methodology is presented by means of the simple coffee production model shown in Gay et al. (2006a). The objective is to generate production and income probability distributions conditional on “expert” subjective information, and the available state of knowledge, for the average coffee producer and estimate the risk that climate variability and change represents (present and future) for this activity. Some representative measures of risk, such as VaR (value at risk), the probability of positive (or greater than a given threshold) income values, as well as some measures of variability and central tendency of production and income and their evolution in time, are reported.

10.3.1 General information regarding coffee production in Veracruz

Agriculture in Veracruz represents 7.9% of the state’s GDP and employs 31.7% of the state’s labor force and coffee production contributes notably to these figures. Veracruz ranks as the second largest national coffee producer. According to the 1992 Coffee Census (Consejo Mexicano del Café, 1996), there are 67,000 producers and 153,000 hectares devoted to coffee production in 82 municipalities generating 300,000 permanent jobs and 30 million daily wages a year. Coffee production in the state is very labor intensive amounting to 80% of the activity’s production costs (Consejo Mexicano del Café, 2001).

Several national and international factors already make this activity vulnerable. 73% of coffee producers in the state are small-scale owning 2 hectares or less and the dominant type of production is “rustic” grown inside the forests in small plantations having low level of technology and a large traditional component.

Considering that in 2001 about half of the municipalities of the state were classified as under very high and high poverty levels[41], and that for most of the municipalities their sources of income depend on agriculture, and in particular on coffee production, this activity is clearly of great socioeconomic relevance for the state of Veracruz.

[41] Consejo Estatal de Población, Xalapa, Veracruz (http://coespo.ver.gob.mx/boletin11dejulio.htm).

Since the 1990s, a combination of national and international factors has lead coffee production in Mexico to a critical situation, compromising the economic viability of this activity for a large number of producers. Currently, producers face a strong low-price competition brought about by the entrance of low-quality production to the international and national coffee markets. This has had a great impact on local producers because, even though Mexican coffee has better quality, processing companies prefer buying cheaper, low-quality coffee and improving its taste using chemicals. In recent years, national and international coffee prices have reached levels so low that a large fraction of producers are not even able to fully cover production costs. A recent study from TechnoServe (2003, in collaboration with McKinsey & Company) reveals that the current crisis is different from all the previous coffee price crises because not only is the price volatile, but in the last 10 years the coffee industry structure has changed with the entrance of cost-efficient competitors, innovations and the increasing demand for Robusta coffee (that has lower production costs than Arabica). This means that while coffee prices will recover from their current historic low, the long term coffee price level will remain below its historical averages and will make this activity unprofitable for many producers.

The prevailing socioeconomic conditions, the limited economic and technical resources that are available to the vast majority of producers and the lack of institutional support are factors that make this activity already vulnerable and potentially limit adaptation capacities. In addition, coffee production has an important component of inertia caused mainly by following factors: increasing or decreasing production levels is a long-term decision (a coffee plant takes up to 6 years to become productive); coffee has to be harvested to maintain plantation health; market distortions (such as subsidies), make coffee supply very inelastic in the short-term to changes in coffee prices, slowing adaptation to changing market conditions (Gay et. al, 2006a). As a result, although coffee prices have dramatically fallen during the past decade, coffee production in the state has remained constant or has even increased. When coffee prices fall, coffee producers partially absorb losses and are compensated to some extent by government subsidies. This has generated a great dependence on government subsidies and has increased coffee producers' vulnerability to changes in government policy - a particularly important factor in the current context of market liberalization. Not surprisingly, coffee prices and changes in government policies are the factors that coffee producers in the state identify as most threatening for this activity, while climate is perceived as a much lesser threat (Conde et al., 2007). Nevertheless, recent studies conducted in other parts of the world have shown that coffee production could be very sensitive to changes in climate variables[42], and this is also true for Veracruz (Eakin et al., 2005). Climate change could be a determinant factor for the physical and economical viability of coffee production in the state that has not been taken into account by coffee producers and government decision-makers.

10.3.2 Simulation model

For simulating coffee production in Veracruz we will adopt the coffee production model shown in Gay et al. (2006a). This is a simple, yet statistically adequate model that considers as independent variables spring precipitation, winter and summer temperatures and minimum wage paid in the state. The model adopts a linear functional form for spring precipitation and minimum wage paid in the state, and a quadratic functional form for temperature variables:

$$\begin{aligned} \Pr od_{coffee} = &-35965262 + 2296270(T_{summ}) - 46298.67(T_{summ})^2 + 658.01618(P_{spr}) \\ &+ 813976.3(T_{win}) - 20318.27(T_{win})^2 - 3549.71(MINWAGE) \end{aligned} \tag{10.1}$$

where:

T_{summ} is the average temperature during Summer.

P_{spr} is the average precipitation during Spring.

T_{win} is the average temperature during Winter

MINWAGE is real minimum wage.

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[42]http://www.grida.no/db/maps/prod/level3/id 1243.htm, http://www.useu.be/Categories/Climate 795 Change/Nov0801UNEPCropyields.html,
http://www.adapcc.org/download/Synthesis_Report_AdapCC_200804.pdf

Statistically adequate time series models for each variable in the coffee production model were estimated in order to approximate the data generating processes including their deterministic and stochastic components, dynamic structure, and distribution. This will permit to correctly simulate the variability shown by the series. Results show that summer temperature can be adequately described as a stationary AR(1) process around a constant, winter temperature can be represented by a deterministic trend plus a white noise process and for spring precipitation a constant plus a white noise process provides an adequate description of this series. Normality tests (Jarque-Bera) were conducted on the stochastic component of the climate variables (i.e. residuals of time series models) and the null hypothesis of normality cannot be rejected at 5% significance level. Therefore a normal distribution with zero mean and a specific variance for each variable will be used to represent the variability of climate variables around a deterministic component. Misspecification tests (not shown here) indicate that the models fitted to climate series are statistically adequate and therefore, provide a good approximation to their data generating process (Spanos and McGurik, 2002).

The time series models estimated for minimum wage indicate the presence of a unit root with a structural change in 1976, and two outliers occurring in 1983 and 1988 all of which correspond to economic crises and presidential changes. Unit root processes are hardly predictable because they contain stochastic trends and their variance increases with time ($t\sigma$). Taking into account the time series properties of this type of processes and the time-horizon of interest for this study (2050), we consider that the observed series does not necessarily convey relevant information about its future evolution[43]. Therefore, this variable will be simulated using a uniform distribution with a time-dependent support in order to describe how its uncertainty increases with time.

[43] Economic variables (as well as their variability) are determined by changes in fundamental factors such as technology and economic and governmental policies, for this reason, economic forecasts are seldom done for time-horizons larger than a few years. Most of economic projections for specific variables and for such large time-horizons are typically done by creating high, medium and low scenarios. A uniform distribution with a support ranging from the lowest to the highest scenario provides a continuum of reasonable possible realizations.

For calculating the income of the average producer, the total number of coffee producers are assumed to remain constant at its current value of 67,000, each producer having 2.23 hectares devoted to this activity. Field studies conducted in the state (Gay et al., 2006b; Eakin, 2003) showed that a producer faces an average cost of $8,000 pesos or $727 US dollars[44] a year per hectare, while the average producer receives government subsidies for an amount of about $750 pesos ($68.2 dollars) a year per hectare. The income of the average producer is calculated as the gross product, minus production costs, plus government subsidies. All economic variables needed to estimate the income of the average coffee producer are simulated using a uniform distribution and are expressed in real terms.

10.3.3 Climate change scenarios for 2050

A total of 32 climate change scenarios of the mean value of each climate variable in the production model were obtained for the Veracruz region for year 2050 using the Pacific Climate Impacts Consortium Regional Analysis Tool[45], considering 7 climate models (CGCM2, HADCM3, ECHAM4, CCSRNIES, GFDLR30, NCARPCM and CSIROMK2B; note that some of them have more than one simulation for a specific emissions scenario) and the four emission scenario families (A1, A2, B1, B2).

Uncertainty in climate change scenarios is particularly large for summer temperature with a range of 3.8ºC, extending from 0.9ºC to 4.7ºC, and for spring precipitation for which different scenarios span a range of possible values from increases of 56% to decreases of 41%. These scenarios clearly illustrate the need for methodologies that can deal with these large ranges of uncertainties in order to make climate change science useful for decision making. For winter temperature the range of uncertainty in climate change scenarios is smaller but still very large, amounting to 1.5ºC.

[44] An exchange rate of $11 pesos per dollar is used in this paper.
[45] http://pacificclimate.org/tools/regionalanalysis/

10.4 Results

10.4.1 Simulation under current climate and economic conditions

A baseline simulation was carried out for approximating the current probability distributions of the state's coffee production and of the income of the average producer. This allows to estimate some measures of the risk that the average producer faces under current conditions and to compare them with the estimates that can be obtained using different probabilistic climate change scenarios. The probability distributions of the input variables for the baseline simulation are parameterized as follows:

- T_{summer} ~ N(24.96, 0.54) [46]
- T_{winter} ~ N(21.6[47], 0.68)
- P_{spring} ~ N(81.35, 28.93)
- *MINWAGE* (daily) ~ U(43, 53)
- Coffee price (per ton) ~ U(2,300, 3,200)
- Production costs (per hectare) ~ U(7,900, 8,100)
- Subsidy (per hectare) ~ U(700, 750)[48]

Table 10.1 presents some descriptive statistics of a simulation of 10,000 realizations of coffee production in Veracruz. These statistics show that coffee production has a small variation with respect to its mean (coefficient of variation of about 12%) implying a low risk in production level. Under current conditions, coffee producers can expect a stable level of production, with a minimum state production greater than 160,000 tons. Figure 10.1 shows the histogram of the simulated coffee production under current conditions.

[46] In this paper, the normal distribution will be defined as N(μ,σ) and the uniform distribution as U(L,U) where L is the lower limit and U the upper.
[47] Winter temperature shows a significant trend, so instead of using the 1961-1990 mean, the conditional mean corresponding to year 2000 was chosen.
[48] All economic variables are expressed in real terms.

The probability density function of coffee is leptokurtic and asymmetric, having a long tail extending to lower values of coffee production. However, as can be seen from Figure 10.1, production levels lower than 300,000 tons have low probabilities of occurring.

Table 10.1. Descriptive statistics of simulated coffee production under current climate conditions and uncertain minimum wage.

Mean	463,641.65
Median	470,523.47
S.D.	52,214.10
IQR	63,573.62
C.V.	11.26%
Range	426,670.43
Max.	587,140.87
Min.	160,470.43
Asymmetry	-0.9612
Kurtosis	4.7598

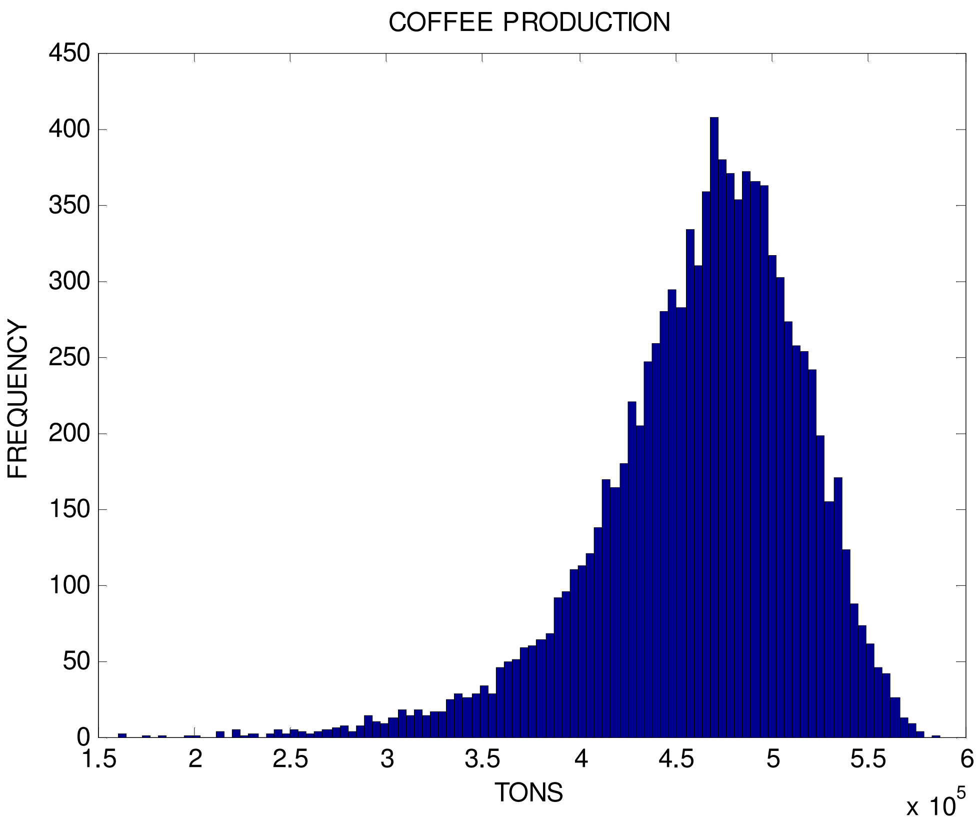


Figure 10.1. Histogram of coffee production in Veracruz under current conditions (uncertainty on prices, wages, production costs and subsidies). 10,000 realizations.

The simulations of net income of the average producer (Table 10.2 and Figure 10.2) show that, even if its mean value is low ($2546.2 pesos or $231.50 dollars), 82.51% of the times the net income is positive and the probability of having income greater than a threshold of $5,000 pesos ($455 dollars) is of 19.58%. Under current climate conditions and this set of economic conditions, the average producer will seldom have losses and his maximum expected loss, as measured by the VaR (value at risk) at 99% confidence level, is of $4,832.68 ($439.33 dollars). Nevertheless, it is important to notice that, given the uncertainty in prices, production costs and subsidies, the net income of the average producer is very variable as shown by its coefficient of variation (110%)[49]. The range of the net income of the average producer amounts to $21,136.70 (1,121.52 dollars), providing another measure of its wide variability. These descriptive statistics show that, even without climate change and with a stable coffee production, coffee producers currently face a high level of risk regarding their income.

[49] The variability of the net income for the average producer is not only caused by the uncertainty in the economic variables of the model. If all economic variables were taken as constants (i.e., no uncertainty), the coefficient of variation would be 53.51%, considerably larger than in the case of production. The range of the net income of the average producer when all economic variables are constant is $19,993.29.

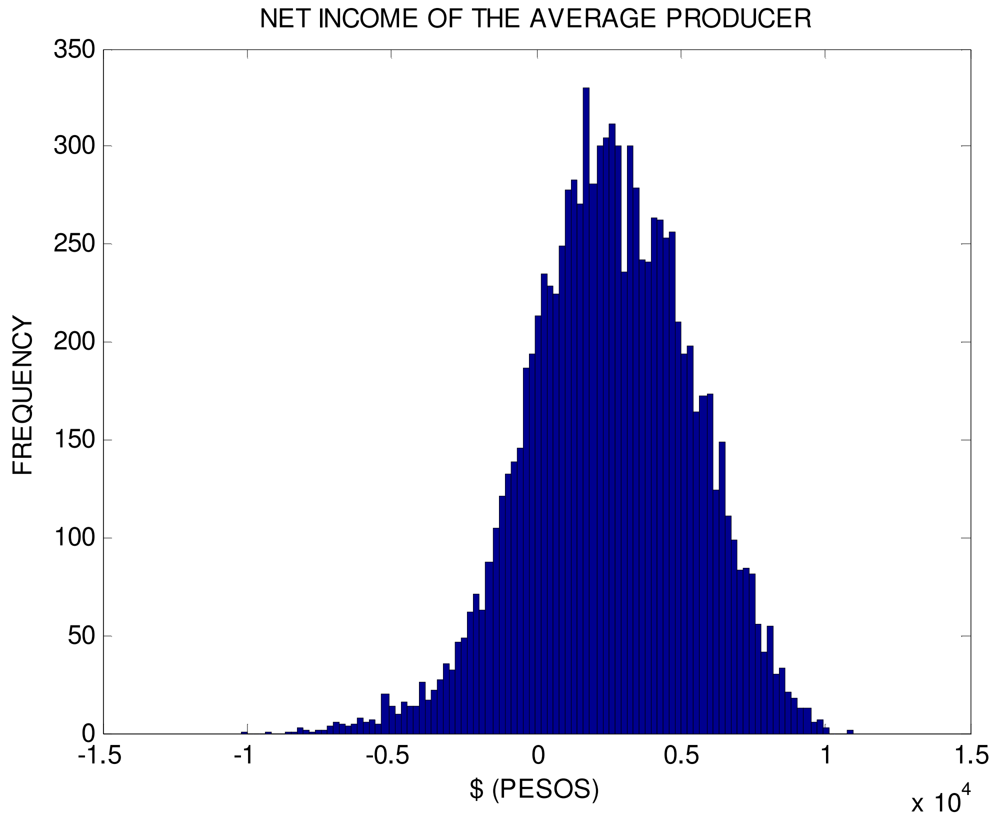


Figure 10.2. Histogram of the net income of the average producer in Veracruz under current climate conditions and the assumptions of economic conditions described in the text.

Table 10.2. Descriptive statistics of simulated net income of the average producer under current climate conditions and the assumptions of economic variables described in the text (figures are in pesos).

Mean	2,546.20
Median	2,555.71
S.D.	2,804.75
IQR	3,835.52
C.V.	110.15%
Range	21,136.70
Max.	10,952.10
Min.	-10,184.87
Asymmetry	-0.2413
Kurtosis	3.1913
VaR (99%)	-4,832.68
P(G|g>0)*	0.8251
P(G|g>5000)*	0.1958

10.4.2 Dynamic simulations of state coffee production and average net income of the average producer under climate change conditions

Seven dynamic simulations are presented in this section, all representing different beliefs regarding future climate change. A control simulation of state coffee production and income of the average producer was carried out under the assumption of no climate change; that is, climate variables are represented using the observed distributions, and uncertainty is only introduced in economic variables. This simulation could also be interpreted as the product of the (subjective) judgment of a decision-maker that ignores climate change.

A second dynamic simulation of coffee production and of the income of the average producer was conducted using a single model (CGCM2) and the B2 emission scenario (Nakicenovic et al, 2000). Notice that using a single emission scenario and model would imply that the decision-maker has an enormous quantity of information in order dismiss all uncertainty, and to assign zero probability to all other scenarios (the probability distribution is degenerated in one point). The main objective of these first two simulations is to compare with other simulations under uncertain climate change scenarios and to provide a rough estimate of the contribution of the uncertainty of economic and climate variables to the time-dependent conditional probability distributions of coffee production and income.

The next five simulations use the Maximum Entropy methodology shown in Gay and Estrada (2010). Two of them correspond to different beliefs ranging from different degrees of “reckless” to “neutral” and up to different degrees of “cautious”.

The information index in Table 10.3 reveals that as the subjectively chosen mean change differs from the central value of the ensemble of scenarios, the more information the decision-maker is assuming to have, and the more uncertainty (as measured by the relative entropy) is dismissed. As an example, consider the decision-maker defined as "reckless 1", the highest levels of information and the lowest of uncertainty are assumed (the information index ranges from 0.46 in summer temperature to 0.66 in spring precipitation). This decision-maker is assuming to have a great amount of information regarding climate change in order to subjectively dismiss such a large part of the uncertainty; therefore, his probabilistic scenarios depend in great manner of his subjective (arbitrary) assumptions.

On the other hand, the choice of the mean average change of the "neutral" agent in Table 10.3 is the central value of the distribution of the ensemble. This mean value translates into the principle of Insufficient Reason which consists in assigning the same probability to each of the possible outcomes. The agent's uncertainty aversion does not lead him to give a greater weight to any of the known possible outcomes. In this case, the information index is zero and the relative entropy reaches its maximum value (1). The information index provides a measure of how much the probability distribution depends on the subjective information provided by the agent, ranging from zero (non informative subjective judgment), to 1 which represents a degenerated distribution in one point and therefore is completely dependent on the subjective information provided by the agent.

Table 10.3 also shows a linear reckless/cautious (uncertainty aversion) index which provides a measure of the level of reckless or cautious attitude a particular average mean change represents. This is a linear function with a range of -1 to 1. The value of minus one represents the most reckless attitude while the plus one value is the most cautious.

In the case of winter and summer temperatures, all scenarios project temperatures to increase, resulting in that coffee production would be negatively affected, and therefore entailing higher risk to coffee producers (see equation 1). Reckless (cautious) attitude is associated with selecting mean temperature changes smaller (larger) than the central value of the distribution of the ensemble. In the case of spring precipitation, scenarios show that increments and decrements are possible. Equation 1 shows that there is a direct and linear relation between coffee production and spring precipitation, consequently reductions in the amount of spring precipitation lead to lower production levels and therefore represent higher risks for coffee producers. Reckless attitude is associated with selecting higher mean values than the central value of the ensemble. In all cases a neutral attitude implies a zero value of the linear reckless/cautious index.

Table 10.3. Average mean changes for summer and winter temperatures and spring precipitation.

Variable	Average mean change	Linear reckless/ cautious index	Relative entropy	Information index	Lambda[a]
Cautious 1					
Winter temperature	2.3ºC	0.73	0.688	0.312	-4.012
Summer temperature	4ºC	0.63	0.783	0.217	-1.168
Spring precipitation	-20mm	0.38	0.758	0.242	0.061
Cautious 2					
Winter temperature	1.8ºC	0.07	0.998	0.002	-0.236
Summer temperature	3.11ºC	0.16	0.987	0.013	-0.234
Spring precipitation	-5mm	0.28	0.961	0.039	0.020
Neutral					
Winter temperature	1.75ºC	0.00	1	0	0
Summer temperature	2.80ºC	0.00	1	0	0
Spring precipitation	6.10mm	0.00	1	0	0
Reckless 1					
Winter temperature	1.1ºC	-0.87	0.50	0.50	6.930
Summer temperature	1.2ºC	-0.84	0.54	0.46	2.415
Spring precipitation	42.93mm	-0.94	0.34	0.66	-0.209
Reckless 2					
Winter temperature	1.5ºC	-0.33	0.95	0.055	1.253
Summer temperature	2.3ºC	-0.26	0.97	0.03	0.381
Spring precipitation	14mm	-0.22	0.98	0.02	-0.014

[a]Lambda is the Lagrangian Multiplier and its value is the rate of change in the objective function (entropy) as the constraint is relaxed.

All the dynamic simulations presented in this section share the same scenarios for the evolution of economic variables. Uncertainty in economic variables is represented by a uniform distribution with linearly increasing support as follows:

- Minimum wage (daily) ~ U(43-$\sum_{i=1}^{t} s$, 53+$\sum_{i=1}^{t} s$); s=10/50
- Coffee price (ton)~ U(2,300-$\sum_{i=1}^{t} p$, 3,200+$\sum_{i=1}^{t} p$); p=1,000/50
- Costs (hectare) ~ U(7,900-$\sum_{i=1}^{t} c$, 8,100+$\sum_{i=1}^{t} c$); c=500/50
- Subsidies (hectare) ~ U(700-$\sum_{i=1}^{t} g$, 750+$\sum_{i=1}^{t} g$); g=100/50

For each climate variables the simulation was carried out as follows:

1) A realization of the corresponding maximum entropy distribution was generated (ΔC)[50].
2) The mean change obtained ΔC was divided by the number of periods to be simulated (50 years) and a linear trend is constructed using this value as its slope.
3) The climate variable is generated obtaining realizations from C_t~ N($\mu + T_t$, σ) where T is the linear trend generated in step 2), μ and σ are the current mean value and standard deviation of the observed variable. In the case of spring precipitation the normal distribution was truncated at zero to avoid the possible occurrence of negative values.
4) For each variable these three steps were repeated 10,000 times.

Tables 10.4 and 10.5 show some of the risk measures that can be obtained by means of this methodology. Given that this methodology provides the conditional distributions of coffee production and income of the average producer, a wide range of risk measures can

[50] The first two dynamic simulations (control and the one based in the CGCM2-B2 scenario) imply degenerated probability distributions, so for these simulations ΔC are constant values.

be produced. The relevant risk measures, and their thresholds, are to be defined according to the informational needs of the stakeholder in order to help in planning and decision-making processes. These can include risk measures such as mean, variance and VaR which are typical for "investment" analysis, or more sophisticated ones such as median, interquartile range and estimates of the probability of reaching a predetermined threshold value. Going over each of these thresholds would trigger an action that has to be defined also by the stakeholder and, as a whole, this set of thresholds would define a time-line for strategic planning.

For example, assume that the relevant risk measures and thresholds for two particular decision-makers are a 10% and 30% decrease in state production, 10% and 50% probability of state production being lower than 250,000 tons, a standard deviation of state coffee production of 60,000 and 80,000 tons, 70% and 60% probability of positive net income for the average producer, and a value for the largest expected loss for the average producer (as measured by the VaR) of $10,000 pesos ($909 dollars). Also assume that each of these decision-makers has different beliefs (reckless and cautious) about the evolution of climate variables[51]. Each of these thresholds would trigger some specific action defined by the decision-maker in order to adapt. This methodology provides estimates of the date each of these thresholds would occur and therefore permits adaptation planning.

This is a sequential process: new simulations should be carried out as new information becomes available. As a clearer picture of climate change and its impacts becomes available, these probabilistic projections are to be revised and updated. The relevance of the proposed risk measures, thresholds and actions should also be regularly evaluated.

Tables 10.4 and 10.5 show that for the "cautious" decision-maker (line labeled as Cautious 2) the first threshold to be reached is a standard deviation of 60,000 tons in state coffee production on the fifth year, followed by the probability of the average producer having a positive income of 70% on the sixth year and 60% in the ninth year. On the 11th

[51] Here we assume a common evolution of economic variables in order to make the results comparable.

year, mean state coffee production reaches the thresholds of a 10% decrease and a standard deviation of 80,000 tons, while the Value at Risk (99%) for the average producer also reaches its pre-defined threshold of $10,000 pesos ($909 dollars). The probability of state coffee production being lower than 250,000 tons reaches the pre-defined thresholds of 10% and 50% on the 14th and 26th years, respectively, while the reduction of 30% in mean state coffee production occurs on the 21st year.

The uncertainty in production (as measured by the standard deviation) generates larger variability (and uncertainty) in the expected income of the average producer. Therefore, lower probabilities of positive income for the average producer follow shortly as well as increments in the value of the VaR. For this type of belief, the rate of decrease in mean state coffee production quickly accelerates as a function of time, similar to the case of the probability of coffee production being lower than 250,000 tons where the increase in this probability accelerates as a function of time.

For the "reckless" decision-maker (line labeled as Reckless 2) the timing of occurrence of the pre-defined critical thresholds is very different. The first threshold to be reached is also a standard deviation of 60,000 tons in state coffee production the 10th year, followed on the 11th year by reaching a 70% probability of having a positive income for the average producer, and a 60% probability in this same risk measure by the 18th year. On year 23, the standard deviation of state coffee production reaches the second pre-defined threshold, and a year later the threshold for the VaR occurs. The second threshold of standard deviation in coffee production occurs on the 23rd year, followed by the thresholds of 10% in the mean state coffee production in the 25th year, 10% probability of state production lower than 250,000 tons in year 35, and a 30% reduction in mean state coffee production in year 49. The threshold of 50% probability of having state production below 250,000 tons never is reached. Notice that for this type of belief, the rate of change of the risk measures is much smaller than for the case of cautious beliefs, most of them being almost linear functions of time.

Tables 10.4 and 10.5 also show how production would develop if no climate change occurs, and therefore provides a baseline for estimating the costs of climate change for this activity. As can be seen from these tables, when no climate change is considered, the economic scenario chosen for all simulations implies a stable production, very similar to the production that can be achieved under current conditions, with a very small increase in variability for the last years of the simulation. The mean/median of the income of the average producer also remains fairly constant, while its variability increases almost linearly, reflecting the uncertainty in prices and production costs. This no climate change scenario produces a slowly decreasing probability of positive income for the average producer, while also the probabilities of having an income larger than $5,000 increase around 35% in 2050 (this is a direct result of uncertainty in prices and costs). Under this scenario, the maximum expected loss (VaR) for the average producer never reaches $10,000 pesos ($909 dollars). Panel h of Table 10.5 presents the estimates of the average economic losses for this activity in Veracruz. The total accumulated present value of the losses up to 2050 are in the range of 3,000 to 14,000 million pesos (from 273 to 1,273 million dollars), depending on the different beliefs assumed by the decision-maker. A 3% discount rate of 3% was used to produce these estimates. These losses represent from 3 to 14 times the current annual value of the state coffee production.

Climate change, through its direct and indirect effects, has two important types of costs: a reduction of production and the associated income of the producer, and an increase in the financial and planning costs caused by a rise in the risk of this activity due to the large uncertainty in climate scenarios.

Lastly, it is also shown in tables 10.4 and 10.5 a simulation (labeled CGCM2 B2) using just one model (CGCM2) and one emission scenario (B2). This simulation represents the impacts assuming degenerated probability distributions in the values obtained by this run (i.e., no uncertainty in climate change projections). Although the central tendency measures of this simulation are similar to those of Reckless 1, there are some fundamental differences. First of all, the CGCM2 B2 discards all other possible climate change scenarios, it assumes to have all the information (no uncertainty, information index equal to 1), while the Reckless 1 simulation uses all possible outcomes, and therefore has an information index value ranging from 0.46 to 0.66; results from the CGCM2B2 simulation are completely dependent on the subjective information (beliefs) of the decision-maker and does not reflect all the state of knowledge regarding climate change scenarios for the region. The CGCM2B2 provides false "confidence" in the estimates as revealed by its low range of uncertainty as measured by all dispersion estimates, and necessarily provides a poor estimation of risk entailing greater dangers for decision-making. This is to reduce uncertainty in an unjustifiable manner: trading uncertainty by ignorance (Schneider, 2003).

10.5 Conclusions

One of the main conclusions of this paper is that, given that objective probabilities in climate change scenarios are not attainable, no "true" impact scenario can be constructed even in a probabilistic framework (see Gay and Estrada, 2010). Uncertainty must therefore be preserved as much as possible in order not to discard in an unjustifiable manner any available information to be used for constructing impact scenarios.

Some of the drawbacks of the methods used for integrating uncertainty in impact assessment are discussed. One of the major pitfalls of the commonly used frequentist approach is that the resulting probability distributions are presented as "objective" facts, when it should be clearly stated that they are all subjective representations of beliefs (Gay and Estrada, 2010). It is argued that subjective beliefs should be brought forward, be clearly stated and that probability distributions should be a meaningful expression of the decision-maker beliefs and not some impersonal, one-size fits all, statistically inadequate device.

This paper presents a new approach for generating climate change impact scenarios that integrate uncertainty and variability, as well as the agent's beliefs or expert judgment, in order to produce tailor-made information for supporting decision-making and planning. It is also shown that time-dependent impact probability distributions (conditional on the available state of knowledge and subjective beliefs) can be constructed and that a great variety of risk measures can be obtained. These risk measures should be aimed to fulfill the information needs of the decision-maker.

The methodology is illustrated with a case study of coffee production in Veracruz (see Gay et al. 2006a). Seven simulations are presented using various maximum entropy probability distributions which represent different subjective beliefs of different possible decision-makers. The time evolution of several risk measures and the date on which they would reach arbitrary thresholds are presented.

The costs of climate change for coffee production are estimated to have a present value in the range of 3,000 to 14,000 million pesos (from 273 to 1,273 million dollars), depending on the different beliefs assumed by the decision-maker. It is important to notice that no adaptation is included and the number of producers is fixed (there are neither entries nor exits of the activity).

It is also argued that climate change, through its direct and indirect effects, has two important types of costs: a reduction of production and the associated income of the producer and; an increase in the financial and planning costs caused by a rise in the risk of this activity due to the large uncertainty in climate scenarios.

Table 10.4. Risk measures obtained for state coffee production

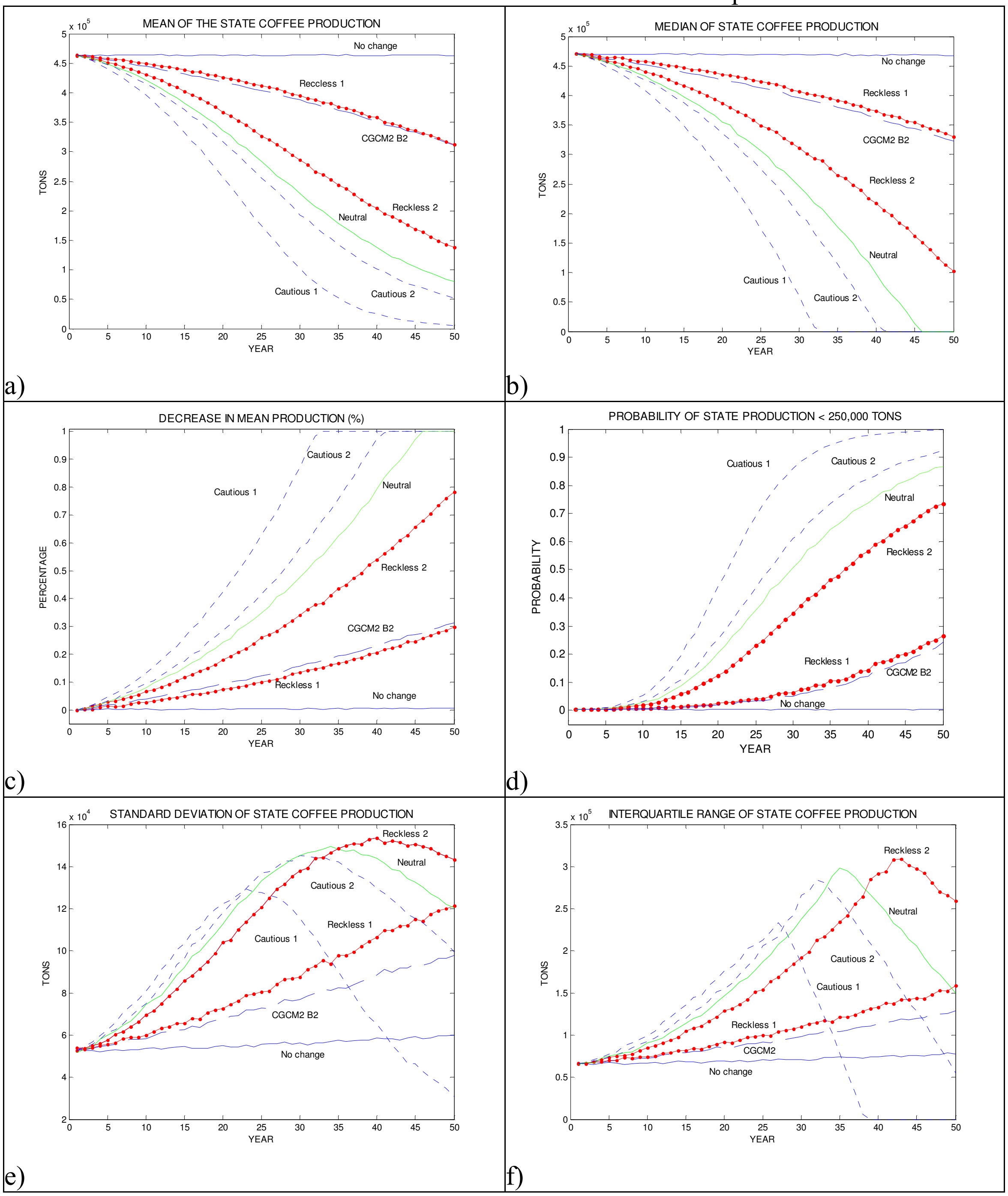


Table 5. Risk measures obtained for income of the average coffee producer in Veracruz.

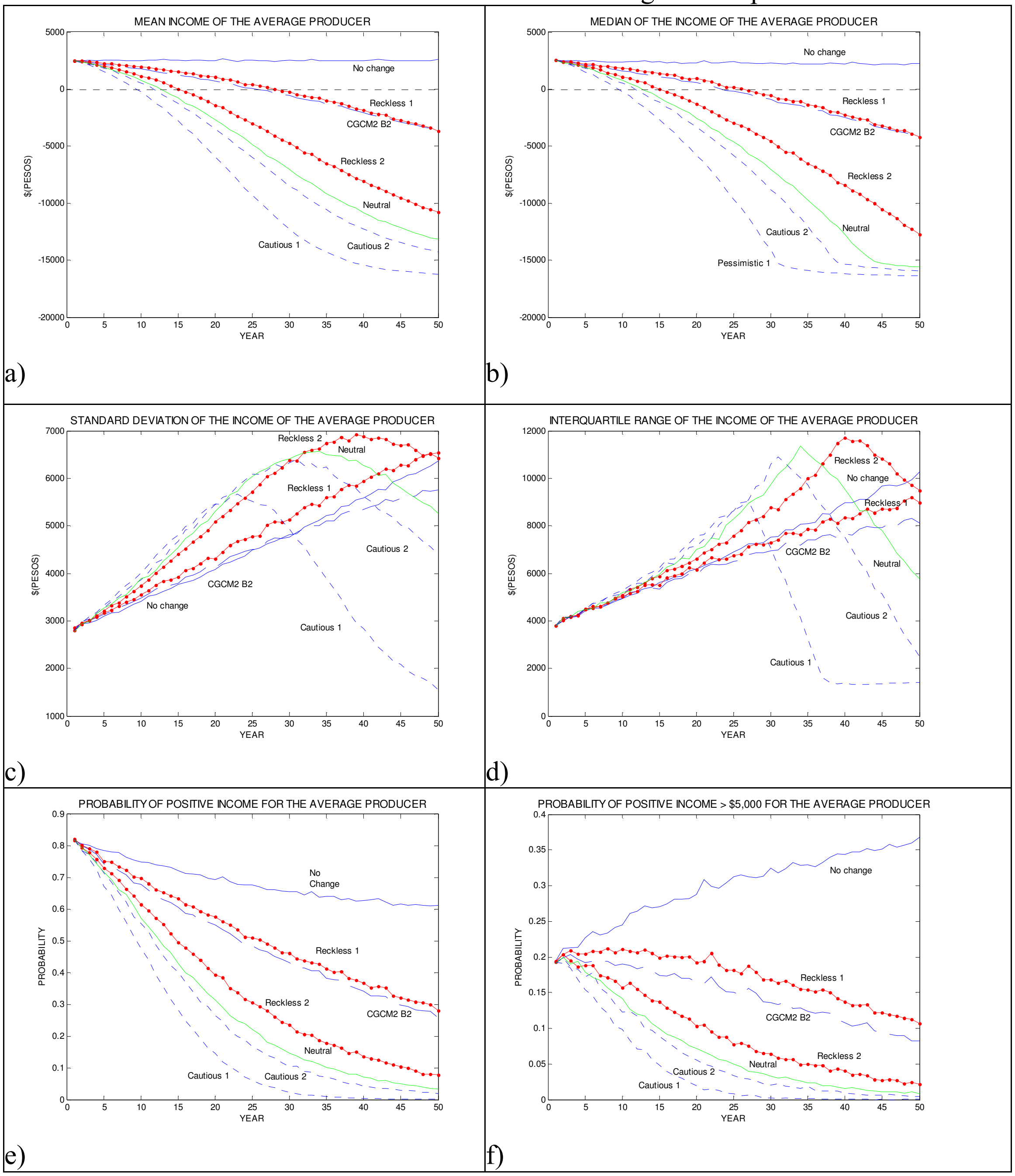
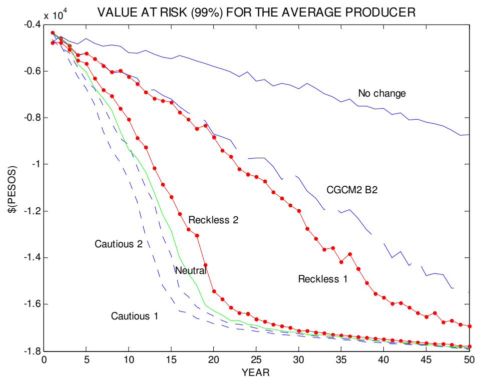


Table 5. Risk measures obtained for income of the average coffee producer in Veracruz (continued).



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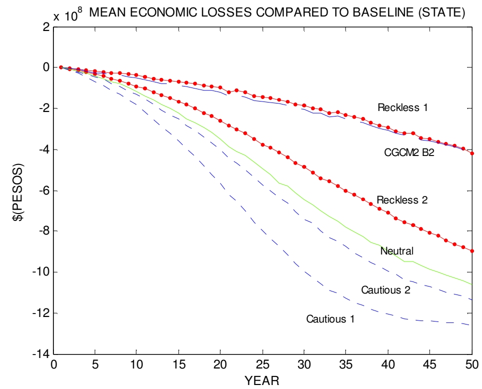

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