UNIVERSITY OF SÃO PAULO
SCHOOL OF ECONOMICS, BUSINESS AND ACCOUNTING
DEPARTAMENT OF ECONOMICS
GRADUATE PROGRAM IN ECONOMICS

**LONG- AND SHORT-RUN CLIMATE IMPACTS ON BRAZIL: THEORY AND
EVIDENCE FOR AGRICULTURE AND HEALTH**

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São Paulo

2012

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EVIDENCE FOR AGRICULTURE AND HEALTH**

Doctoral dissertation submitted to the
Department of Economics of the School of
Economics, Business and Accounting at the
University of São Paulo in partial fulfillment
of the requirements for the degree of Doctor of
Sciences.

Advisor: Prof. Dr. Denisard Cnéio de Oliveira Alves

Corrected Version

(original version available on the unit of the program)

São Paulo

2012

FICHA CATALOGRÁFICA

Elaborada pela Seção de Processamento Técnico do SBD/FEA/USP

Pereda, Paula Carvalho

Long- and short-run climate impacts on Brazil: theory and evidence for agriculture and health / Paula Carvalho Pereda. -- São Paulo, 2012. 202 p.

Tese (Doutorado) – Universidade de São Paulo, 2012.
Orientador: Denisard Cnéio de Oliveira Alves.

1. Microeconomia 2. Economia ambiental 3. Economia agrícola 4. Economia da saúde 5. Econometria I. Universidade de São Paulo. Faculdade de Economia, Administração e Contabilidade. II. Título.

CDD – 338.5

**To my family,
in honor of Oswaldo Carvalho (*in memoriam*)**

ACKNOWLEDGEMENTS

First of all I would like to thank my advisor Professor Denisard Alves for the support, dedication, patience, friendship and comprehension during the development of this thesis. It was an honor to have shared his knowledge and wisdom in this time we have worked together.

To Professor Eduardo Haddad, Bruno Giovannetti and Marcos Rangel, members of the qualifying examinations, for the contributions, critics and suggestions that made the difference in the preparation of this work.

To Professor José Paulo Chahad and family, for the friendship and help during the most difficult moments of this experience.

To Professor Elizabeth Farina and Danilo Iglioni and colleagues from NEREUS for the support during the doctoral studies.

To all employees (graduate secretary and coordination, and economics department) especially to Alda, Bela and Renata for the friendship and trust, and to Valéria, Cida and Pinho for the attention and professionalism.

To USP and FEA for the relevant role in my academic and personal experiences.

To CNPQ and *Instituto Nacional de Ciência e Tecnologia para Mudanças Climáticas/Rede CLIMA* for the financial support. To INPE and INMET for providing me with the data on climate forecast and observation.

To people from IRI Summer Institute of 2011, ICTP and SEA, especially to M.D. Gilma Mantilla, Dr. Rachel Lowe and Dr. Giuseppe Arbia for the contributions and financial support to the courses in their institutions.

To my dear friend Andrea Lucchesi for the company, patience, attention and help during the whole doctoral studies and especially during the development of this thesis.

To Marina Gontijo, Taci Muniz, Ana Baruffi, Henrique Vinhais, Weslem Faria, Juliana Speranza, Carolina Garcia, Gustavo Andrey, Priscilla Tavares and Eduardo Sanchez, for the friendship and direct help on this work, either by suggestions and critics or by helping with databases.

To friends from Guarulhos, the girls from the undergraduation (in the name of Ju Honda and Katia), friends of the graduate studies and to everybody who contributed, directly or indirectly, to this work. A special acknowledgement to my dear friends, Fernando and Marina Cerqueira, whose weddings I could not participate due to my doctoral studies.

Finally, to my family – my parents Luiz and Marcia, my siblings Juliana and Luiz Eduardo and their families, Vado, my grandmothers – and to my Edu for the love, affection, dedication, support, patience, respect, trust and so many other things that would not fit into a simple thank you page. You are everything to me!

AGRADECIMENTOS

Primeiramente agradeço ao meu orientador e professor Denisard Alves pelo apoio, dedicação, paciência, amizade e compreensão em todo o processo de desenvolvimento desta tese. Foi uma honra compartilhar da sua sabedoria e conhecimento em todo o tempo em que trabalhamos juntos.

Aos professores Eduardo Haddad, Bruno Giovannetti e Marcos Rangel, membros da banca de qualificação e seminário de tese, pelas contribuições, críticas e sugestões que fizeram a diferença na elaboração deste trabalho.

Ao professor José Paulo Chahad e família, pela amizade e ajuda nos momentos mais difíceis desta empreitada.

Aos professores Elizabeth Farina e Danilo Iglioni e aos colegas do NEREUS pelo apoio durante o doutorado.

Aos funcionários da secretaria de pós-graduação, da coordenação e do departamento de Economia, em especial agradeço à Alda, Bela e Renata pela amizade e confiança de sempre, e à Valéria, Cida e Pinho pela atenção e profissionalismo.

À USP e FEA pelo papel fundamental na minha formação acadêmica e pessoal.

Ao CNPQ e Instituto Nacional de Ciência e Tecnologia para Mudanças Climáticas/Rede CLIMA pelo suporte financeiro. Ao INPE e INMET pelo fornecimento dos dados climáticos de previsão e de observação.

Ao pessoal do IRI Summer Institute de 2011, do ICTP e do SEA, em especial à Dra. Gilma Mantilla, Dra. Rachel Lowe e Dr Giuseppe Arbia pelas contribuições e apoio financeiro para os cursos que fiz em suas instituições.

À querida amiga Andrea Lucchesi pelo companheirismo, atenção, paciência e ajuda ao longo do doutorado e do desenvolvimento da tese.

À Marina Gontijo, Ana Baruffi, Henrique Vinhais, Weslem Faria, Juliana Speranza, Gustavo Andrey, Carolina Garcia, Priscilla Tavares e Eduardo Sanchez, pela amizade e ajuda direta no desenvolvimento deste trabalho, seja por sugestões e críticas ou ajuda com base de dados.

Aos amigos de Guarulhos, às meninas da faculdade (em nome da Ju Honda e Katia), ao pessoal da pós-graduação e a todos que contribuíram, diretamente e indiretamente, com amizade, companhia e compreensão. Em especial, um agradecimento aos amigos Fernando e Marina Cerqueira, cujos casamentos eu não pude participar em virtude do meu doutorado.

E, finalmente, à minha família – meus pais Luiz e Marcia, meus irmãos Juliana e Luiz Eduardo e suas famílias, Vadão, minhas avós – e ao meu Edu pelo amor, carinho, dedicação, apoio, paciência, respeito, confiança e tantas outras coisas que não caberiam em um singelo agradecimento. Vocês são tudo para mim!

ABSTRACT

Climate has relevant impacts on economic activities and human well-being. This study aims to contribute to the identification and measurement of these impacts on the agricultural markets and health.

With regard to health, dengue fever – a climate-sensitive disease – is analyzed, as it affects thousands of Brazilians every year, generating large costs in both private and public markets (approximately US\$800 million in Brazil in 2011). Thus, chapter 2 addresses the impact of climate on the risk of dengue fever in Brazil, modeling dengue incidence as a risk function estimated using count data models applied to the outbreak of dengue epidemics in 2010 and controlling for likely endogeneities.

The results corroborate the relevance of climate variables in explaining dengue incidence in Brazil. Moreover, if climate change occurs as expected, the results suggest a potential added risk for central-southern areas in Brazil and a risk reduction for northern areas of the country. Short-term deviations from normal rainfall conditions in summer also seem to increase the risk of dengue when compared to normal rainfall conditions. Other results suggest the non-effectiveness of local expenditures for epidemiological surveillance and the need of integrated actions to control the disease.

When it comes to agricultural markets, two important hypotheses are tested: i) farmers only observe the average climate conditions of their region when deciding the type and amount of crop/animal to grow/raise (Chapter 3); ii) weather diversions from normal climate conditions might deviate farmers from their optimal profits, causing inefficiencies (Chapter 4). Both hypotheses are not rejected by the data. The modeling approach used is the translog profit frontier approach.

The results indicated that if the climate change forecasts are confirmed, almost all the agricultural products in Brazil will be negatively affected, especially production of cattle products (beef and milk), coffee and maize. The only product that shows a positive effect is soybeans, probably due to its current high adaptability to different climate patterns. Use of irrigation is the main compensation instrument to reduce the expected climate change impacts. However, technological instruments such as use of transgenic seeds, cattle confinement, along with the increase in tillage, are also important adaptation measures to climate change.

The analysis of the determinants of the efficiencies calculated suggests that droughts and cold stresses cause harmful effects to agriculture in Brazil. In 2006, the estimated loss from rainfall anomalies is approximately 15 billion dollars (in 2011 values). The southern and midwestern regions are slightly more vulnerable than the other regions. Assuming the extreme hypothesis of drought and cold stress occurrence overall in Brazil, the total profit loss is about 81 and 35 billion dollars, respectively. These losses can be mainly mitigated by the intense use of an insurance instrument, but the participation of farmers in the agricultural insurance market in Brazil is still very low.

RESUMO

O clima impacta diversas atividades econômicas e humanas. Esta tese tem o objetivo de contribuir para a identificação e mensuração de alguns destes impactos, com foco nos mercados agrícolas e na saúde.

Com relação à saúde, o dengue, que é uma doença sensível ao clima, é analisado uma vez que afeta milhares de brasileiros todos os anos e causa expressivas perdas para os mercados privados e para a saúde pública (cerca de US\$800 milhões no ano de 2011 para o Brasil). Desta forma, o Capítulo 2 busca entender o impacto do clima no risco de dengue no país por meio da modelagem e estimação do risco de dengue usando dados da epidemia de 2010 e modelos de dados de contagem com controle das endogeneidades detectadas.

Os resultados corroboram a relevância das variáveis climáticas na explicação da incidência de dengue no Brasil. Ademais, se as mudanças climáticas ocorrerem da forma esperada, os resultados sugerem um aumento do risco na região do Centro-Sul brasileiro e redução do risco no Norte-Nordeste. Desvios de curto prazo da precipitação no verão também parecem potencializar o risco da doença, quando comparado ao risco em condições pluviométricas normais. Outros resultados sugerem que as despesas municipais com vigilância epidemiológica não são efetivas no combate ao dengue e ações integradas são necessárias para o controle da doença no curto-prazo.

Com relação aos mercados agrícolas, duas importantes hipóteses são testadas: i) fazendeiros apenas observam as condições climáticas médias de suas regiões no momento em que decidem o que e quanto produzir (Capítulo 3); ii) desvios climáticos de curto prazo podem afastar os fazendeiros de seus lucros ótimos, causando ineficiências (Capítulo 4). Ambas as hipóteses não são rejeitadas pelos dados. Para tal teste, estimou-se uma equação de fronteira de lucro com a especificação translog.

Os resultados indicaram que, se confirmadas as mudanças climáticas, praticamente todos os produtos agrícolas serão negativamente afetados, especialmente a produção de leite, carne bovina, café e milho. O único produto positivamente impactado seria a soja, provavelmente devido à sua adaptabilidade a diferentes climas. O uso de técnicas de irrigação parece ser um importante instrumento de adaptação a tais mudanças. Todavia, outros instrumentos tecnológicos, tais como o uso de sementes transgênicas, confinamento de gado, assim como o uso de plantio direto, também se mostraram importantes técnicas de adaptação à evolução esperada do clima.

A análise dos determinantes da eficiência agrícola sugere que secas e ondas de frio impactam negativamente a agricultura no Brasil. Em 2006, a perda agrícola estimada relacionada à falta de chuvas foi de aproximadamente 15 bilhões de dólares (em valores de 2011). As regiões Sul e Centro-oeste são sensivelmente mais vulneráveis do que as demais regiões. Assumindo a hipótese extrema de ocorrência de seca e onda de frio em todo o país, as perdas estimadas de tais eventos são da ordem de 81 e 35 bilhões de dólares, respectivamente. Essas perdas podem ser mitigadas pelo uso de seguros agrícolas, porém a participação de fazendeiros no mercado de seguro rural no Brasil é ainda muito baixa.

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LIST OF ABBREVIATIONS, INITIALISMS AND ACRONYMS

AIC: Akaike information criterion

BIC: Bayesian information criterion or Schwarz criterion

CC: Climate Change

CNPQ: *Conselho Nacional de Desenvolvimento Científico e Tecnológico* (National Counsel of Technological and Scientific Development)

CPTEC: *Centro de Previsão de Tempo e Estudos Climáticos* (Department for Weather Forecasting and Climate Studies)

CRU: Climate Research Unit

EMBRAPA: *Empresa Brasileira de Pesquisa Agrícola* (Brazilian Agricultural Research Agency)

EPA: Environmental Protection Agency

FAO: Food and Agriculture Organization

FEA: *Faculdade de Economia, Administração e Contabilidade* (School of Economics, Business and Accounting)

FINBRA: *Finanças do Brasil* (Finance of Brazil)

GDP: Gross Domestic Product

GHG: Greenhouse Gas

GLM: Generalized Linear Model

GMM: Generalized Method of Moments

HHI: Herfindahl-Hirschman Index

IBGE: *Instituto Brasileiro de Geografia e Estatística* (Brazilian Institute of Geography and Statistics)

IC: *Intervalo de Confiança* (Confidence Interval)

ICTP: International Centre for Theoretical Physics

IPCA: *Índice de Nacional de Preços ao Consumidor Amplo* (National Consumer Price Index)

IPEA: *Instituto de Pesquisa Econômica Aplicada* (Institute for Applied Economic Research)

INMET: *Instituto Nacional de Meteorologia* (National Institute of Meteorology)

INPE: *Instituto Nacional de Pesquisas Espaciais* (National Institute for Aerospace Research)

IPCC: Intergovernmental Panel on Climate Change

IRI: International Research Institute for Climate and Society

MAPA: *Ministério da Agricultura, Pecuária e Abastecimento* (Ministry of Agriculture)

ML: Maximum-likelihood

MLE: Maximum-likelihood Estimation/Estimator

MM: Millimeter

MS: *Ministério da Saúde* (Ministry of Health)

MW: Minimum Wage

NASA: National Aeronautics and Space Administration

NB: Negative Binomial

NDVI: Normalized Differenced Vegetation Index

NEMESIS: *Núcleo de Estudos e Modelos Espaciais Sistêmicos* (Research Network on Spatial Economic Analysis)

NEREUS: *Núcleo de Economia Regional e Urbana da USP* (The University of São Paulo Regional and Urban Economics Lab)

OLS: Ordinary Least Square

PACS: *Programa de Agentes Comunitários de Saúde* (Community Health Officers Program)

PAM: *Pesquisa Agrícola Municipal* (Municipal Agricultural Survey)

PDF: Probability Density Function.

PNAD: *Pesquisa Nacional por Amostra de Domicílios* (National Household Sample Survey)

PNCD: *Programa Nacional de Controle da Dengue* (National Dengue Control Program)

PSF: *Programa Saúde da Família* (Family Health Program)

SINAN: *Sistema de Informação de Agravos de Notificação* (Information System for Disease Notification)

SUS: *Sistema Único de Saúde* (Brazilian Public Health System)

TE: Technical Efficiency

UN: United Nations

USDA: United States Department of Agriculture

USP: *Universidade de São Paulo* (University of São Paulo)

VC: Variance-Covariance

WHO: World Health Organization

INTRODUCTION

Climate has important impacts on economic activities and human well-being perspectives. These influences are mainly related to ecosystem equilibrium, water quality and availability, biological aspects associated with human health, as well as agricultural production, and rural development.

This study focuses on the measurement of specific climate effects on agricultural markets and health issues. With these concerns in mind, two different impacts of climate are considered: short- and long-term, as briefly summarized below:

Agricultural Markets: The climate itself is a direct input for crop and animal production, impacting land use configuration (long-term effect). Moreover, climate is an important determinant of crop/livestock failure and loss of productivity (short-term effect).

Health: Climate can influence human health in various forms. Infectious diseases are examples of climate-sensitive health problems. Climate conditions affect the dynamics of vector-borne disease transmission due to their relation with the breeding, survival, distribution and reproduction of vectors. Consequently, climate alterations have the potential to modify the geographical distribution of diseases (long-term effect), as well as to influence the occurrence of epidemics (short-term effect) (GAGE *et al.*, 2008). Dengue fever is analyzed, as it is the most relevant infectious disease in Brazil.

Economic theory provides useful perspectives and theoretical tools to understand the role of climate on agriculture production and health, using dengue outbreaks and agricultural markets as case studies. Thus, the short- and long-term climate impact on dengue is analyzed in a risk function of the disease, controlling for potential endogeneity of neighborhood transmission, time dependence, and expenditures for epidemiological surveillance. When it comes to the climate effects on agricultural markets, a profit frontier approach is used. The basic hypotheses assumed are that average climate conditions are relevant for farmers' decisions, as they only observe past climate information. Once the farmers decided which and how much crop/product to grow/raise, extreme weather events might deviate them from optimal profit through potential harvest failures, livestock losses and change in productivity.

The measurement of these causal effects allows forecasting the potential partial climate effects on communities and producers. In addition, it also permits propositions on effective decisions in the public sector to reduce the possible harm from climate in Brazil. Thus, this thesis intends to link two relevant agendas: managing the climate related risks of today (short-term effect) while improving understanding of the risks of tomorrow (long-term effect). Based on this view, the following questions are addressed:

i. Dengue fever and climate interaction in Brazil:

- a. Does the dengue risk depend on short- and long-run climate conditions?
- b. How is the susceptibility to dengue fever expected to change due to short-term climate conditions?
- c. How is the susceptibility to dengue fever expected to change due to climate change?
- d. Are the current public policies reducing dengue risk?
- e. How could government interventions minimize the possible harmful climate effects?

ii. Agriculture and climate interaction in Brazil:

- a. Do average local climate conditions influence farmers' output decisions?
- b. How does the expected climate change affect farmers' profit and production?
- c. Which instruments can be used to compensate such expected changes in future climate?
- d. Do extreme weather events influence farmers' efficiency in generating profits?
- e. What are the relevant actions that might increase farmers' efficiency in the short-run?
- f. What is the potential size for a rural insurance market for extreme weather?

The answers to these questions not only contribute to the current debate on how expected climate change might influence future human health and human activities, but also address the proposition of short-term actions to reduce the climate variability effects on poor communities. Climate variations are expected to adversely affect food production and health in some parts of the country, generating important monetary

losses that will be relatively higher for small farmers and poorer populations. Due to this problem of uneven effect, public intervention is needed to stimulate the market to produce alternatives.

Thus, the conclusions reached here are expected to help governments manage interventions in order to minimize the risk of dengue transmission, crop/livestock failures and changes in farming production. In particular, governments should be prepared particularly to assist and support poorer communities when climate impacts them negatively. Moreover, the optimal government intervention to reduce potential harmful climate impacts should rely on consistent estimations of the specific issue concerned.

Chapter organization

This thesis is divided into five chapters. The first chapter is descriptive and shows evidence of observed and forecast climate changes, and also explores the main climatic differences of Brazilian regions.

Chapter 2 presents the climate impacts on dengue fever incidence in the country. The analysis concentrates on climate's importance to the risk of dengue epidemics and also tests the partial influence of social vulnerabilities and current public policies on the disease incidence. The data analyzed cover the most recent epidemics in the country (2010).¹ The expected impact of climate change on geographical distribution of dengue fever is calculated for Brazil and the relevance of using seasonal forecasting tools to predict dengue risk (in the following year) is analyzed. These forecasting tools can be used to help governments plan prevention interventions to reduce the disease risk.

Chapters 3 and 4 discuss the agricultural model for identifying marginal climate impacts on this economic activity. The former chapter seeks to model the longer-term effects in order to estimate the importance of climate patterns on farmers' decisions in the country. Technological variables are also included as quasi-fixed inputs in this model to measure their marginal impact in guaranteeing farmers' income by compensating climate change's potential harmful effects.

Chapter 4 develops the model to identify how extreme weather events, interpreted as climate deviations from long-term trends, affect farmers' efficiency and profits. This

¹ The last Brazilian Demographic Census was collected in 2010. This is the most detailed and complete survey in the country when it comes to population information and measurement of social infrastructures.

measurement allows the calculation of the maximum propensity to pay for extreme events mitigation instruments (proxy for the size of weather insurance market), as well as identifies important actions that increase farmers' efficiency.

Finally, Chapter 5 summarizes all the findings from the previous chapters and discusses future avenues for investigation, indicating possible government actions needed to deal with the problems raised by the thesis.

Note on tables, figures, equations, and appendices

The objects, tables and figures are identified by two digits: the first refers to the chapter number, and the second to the ordination along the chapter. Figure 3.2, for example, is the second figure from Chapter 3. The same logic is used to identify the equations throughout the text.

Regarding the appendices, the identification also indicates the same logic; however the letter "A" precedes the numbering, both in tables and graphs, as well as the appendices' identification.

1. CLIMATE DESCRIPTION

This short chapter presents some evidence of observed and forecast climate changes and explores the main climatic differences of Brazilian regions. Many of the definitions given here are used in the following chapters, mainly when the climate variables of the modeling are described.

First of all, it is important to understand the temporal differences in how the climate can be assessed, as the introduction of this thesis emphasizes. There are two important distinctions:

- *Long-term climate conditions*, which are the average conditions of regions, where patterns can be identified, such as: the average precipitation in the Amazon Forest is higher than in the Northeast semiarid region, although both regions have the same high average temperatures throughout the year. Sections 1.1 and 1.2 show some evidence suggesting that the average climate conditions have changed and are changing² in the world and also in Brazil;
- *Short-term climate variations*, which represent the annual climatic deviations from long-term conditions. These deviations are usually dominated by inter-annual and seasonal variations and are observed due to the oscillations of the Earth's climate system regarding weather patterns at the local, regional and global levels.³

Most scientists agree that climate change in the future is expected to be a multifaceted phenomenon, involving evolution in the distribution of climate over time, which might affect long-term average conditions as well as the variation of climate (IPCC, 2001; 2007). This thesis takes into account both concepts in the modeling, which can bring important evidence for future interventions.

Considering these distinctions, the following sections briefly present climate evidence for the world and for Brazil to show the importance of understanding the impacts if the predicted changes in climate are confirmed.

² Those structural changes (climate changes) might have external causes (changes in the orbit of the planets), internal causes (changes in oceanic circulation, composition of atmosphere gases), and human causes (burning fossil fuels, deforestation, greenhouse gas emissions). See Nieuwolt and McGregor (1998), *apud* Mendonça (2003), and Kalkstein and Valimont (1987).

³ The two main causes of climate variability are the influences of biological phenomena and extreme episodic events (CONFALONIERI, 2003),

1.1 Observed changes in climate

The observation of historical annual temperature values (and anomalies), published by the Climate Research Unit (CRU), together with Hadley Centre (UK Met Office), from 1860 to 2006, supports the idea of climate evolution during the last 150 years.

Figure 1.1: Temperature anomalies (deviation from long-term average) in degrees Celsius (°C), 1860 to 2006.

Source: CRU (2011).

Figure 1.1 indicates a rising trend in average temperature during the period. The period between 1995 and 2004 was the warmest period in the sample (11 of the 12 years from 1995 to 2006 were among the warmest years since 1860). From 2000 to 2005, the average temperature was 0.48 °C above the long-term average and 2005 was the second warmest year of the whole sample.

When it comes to the global rainfall, evidence of changes is also observed globally. The evidence is weaker in terms of long-term changes, but stronger in relation to the variation of the rainfall patterns. According to IPCC (2007), trends from 1900 to 2005

have also been observed in precipitation amount: on the one hand an increase in rainfall is observed in eastern areas of North and South America and northern Europe and central Asia; on the other hand, some areas have experienced lower rainfall, such as southern Asia and Africa, the Mediterranean and Sahel.

There is also evidence of an increase in extreme event frequency, such as droughts, floods, heat and cold waves, hurricanes and other storms (IPCC, 2001). The percentage of drought areas seems to be increasing globally.⁴ However, it is harder to identify changes in the pattern of global extreme weather events.

Marengo and Valverde (2007) and Marengo (2007) gathered more evidence of changes in climate patterns in Brazil over the last century. The first is the increase in average and extreme temperatures in Brazil. The country's average temperature increased about 0.75 °C at the end of twentieth century in comparison with the beginning of the century (Figure 1.2). The warmest year in the historical series was 1998, 0.95 °C higher than the long-term average.

Figure 1.2: Anomalies in temperature in °C (above) and rainfall in % (below), Brazil, 1901-1998.*

* The reference period for calculating anomalies (deviation from average) is 1961-1990. The black line represents the 11-year moving average (25 °C for temperature; 1,780 mm/year for precipitation). Source: Hulme and Sheard (1999).

The second piece of evidence relates to the higher frequency of extreme temperatures in Brazil. Marengo (2007) affirms that studies regarding the changes in extreme temperature events are still not conclusive in South America, mostly due to the lack of good high frequency data for the region. However, some authors have found positive

⁴ Current examples of the occurrence of those events are the European heat wave in 2003; hurricanes in North America in 2005; extreme winter in Europe and Asia in 2006; Brazilian hurricane Catarina in 2004; drought in the Amazon in 2005; and droughts in the southern region of Brazil in 2004, 2005 and 2006.

trends in the frequency of hotter nights (both in winter and summer) and negative trends for the frequency of cold nights during winter in South America (VINCENT *et al.*, 2005; ALEXANDER *et al.*, 2006; *apud* MARENGO, 2007).

The third indication comes from precipitation frequency in the country. Groisman *et al.* (2005) and Carvalho *et al.* (2002) found a systematic increase in precipitation extremes in the South and Northeast regions of Brazil. In the Southeast, there has been an increase in the frequency of intense rainfall since 1940.⁵

The observation of historical data suggests that the average climate as well as climate variability seem to be changing in the past century. Based on this observation and hypotheses about the future economic and environmental issues, climatologists have been forecasting the main climate variables: temperature and precipitation. The next section summarizes the main forecasts that, if confirmed, might affect relevant sectors of the economy.

1.2 Climate change forecasts

Since the Intergovernmental Panel on Climate Change's Fourth Assessment Report – AR4 (IPCC, 2007), climate change discussion by scientists has expanded. If the climate evolves as the forecasts suggest, the size of the impacts and potential need for adaptation measures become relevant agendas for governments. In order to predict the global temperature increase, the IPCC (2007) report considered different scenarios of greenhouse gas (GHG) emissions. The global estimates vary from an increase of 1.8 to 4.0 °C from 2090 to 2099 relative to the average temperature of 1980-1999.

Table 1.1: Projected global temperature change in °C, 2090-2099 relative to 1980-1999.

Case	Best estimate	Likely range
Constant year 2000 concentrations	0.6	0.3 - 0.9
B1 scenario [*]	1.8	1.1 - 2.9
A1T scenario [*]	2.4	1.4 - 3.8
B2 scenario [*]	2.4	1.4 - 3.8
A1B scenario [*]	2.8	1.7 - 4.4
A2 scenario [*]	3.4	2.0 - 5.4
A1FI scenario [*]	4.0	2.4 - 6.4

Source: IPCC (2007).

^{*}The scenarios are fully described in IPCC (2000) and explore alternative development pathways: A1: Assumes a world of very rapid economic growth with three groups of alternative directions of

⁵ Carvalho *et al.* (2002) found that in São Paulo floods occurs more frequently during *El Niño* periods, as the region is sensitive to the so-called “South Atlantic Convergence Zone”.

technological change: fossil intensive (A1FI), non-fossil energy resources (A1T) and a balance across all sources (A1B); B1: Describes a convergent world, with more rapid changes in economic structures toward a service and information economy; B2: Describes a world with intermediate population and economic growth and local solutions to economic, social, and environmental sustainability; and A2: Describes a very heterogeneous world, high population growth, slow economic development and technological change.

The climate change information in Brazil is produced by CPTEC/INPE, the department for weather forecasting and climate studies of the National Institute for Space Research. The following table shows the predictions of three models run by INPE⁶ for two of the IPCC scenarios: A2 (Pessimistic: High emissions); and B2 (Optimistic: Low emissions), from 2040-2069 and 2070 to 2099.

Table 1.2: Projected temperature and precipitation change, 2040-2069 and 2070-2099 relative to 1976-2005, by season, Scenarios A2 and B2.

Season / climate variable	A2		B2	
	2040-2069	2070-2099	2040-2069	2070-2099
Rainfall (in mm)				
Fall	-4.15	-5.35	0.07	-2.84
Spring	-1.83	-5.55	-2.25	-0.54
Summer	-0.65	-7.66	2.39	2.18
Winter	-2.03	-3.29	-2.30	-2.52
Temperature (in °C)				
Fall	1.96	3.56	1.62	2.49
Spring	2.26	3.90	1.94	2.78
Summer	1.93	3.48	1.55	2.29
Winter	2.10	3.86	1.86	2.76

Source: CPTEC-INPE.

In terms of temperature anomalies, both scenarios indicate an average increase in temperature for both periods: 2040-2069 and 2070-2099. The optimistic scenario (B2) indicates average variation of about 1.55 to 2.78 °C among seasons; and the pessimistic scenario (A2) shows greater average variation in temperature, from 1.93 to 3.9 °C.

When it comes to precipitation anomalies, both scenarios indicate less rain in the spring and winter seasons (normally the driest seasons in Brazil for most regions). The B2 scenario forecast envisions more average rainfall in Brazil during summer in both time periods, while in scenario A2, drier summers are expected.

⁶ CPTEC/INPE uses regional models, which downscale the global models (HadRM3P Model; Eta/CPTEC Model; and RegCM3 Model). Correlation anomalies among the models are calculated in order to detect consistent signals for the predictions. The output of the models is an average of the combined results from three forecasting model, this is called “multi-model ensemble technique” (UK MET Office, 2012).

IPCC (2007) report mentions that natural atmospheric disasters are likely to continue increasing in Brazil, especially storms and heavy rainfall in the southern and southeastern regions of the country. The report also points to the worsening of droughts in the Northeast and increase in droughts in the North and Midwest regions. However, these deviations are more difficult to detect in forecasts.

1.3 Climate in Brazilian regions

The historical climate data for Brazil were obtained from the National Meteorology Institute (INMET), under the Ministry of Agriculture (MAPA). The institute collects information about average, minimum and maximum temperature, total precipitation (in millimeters and rainy days) and relative humidity by weather stations, whose spatial distribution is presented below:

Figure 1.3: Brazilian weather stations, INMET, 2010.

Source: Dataset from INMET. Prepared by the author.

Brazil has a network of weather stations that covers much of the coast, but has a low density in the interior, especially in the North and Midwest regions.

To transform the data from the weather stations into municipal⁷ data, the kriging method of interpolation is used (HAAS, 1990). This method assumes that each geographical coordinate is a realization of a spatial process. It allows the interpolation of data with flexibility to specify the covariance between the outputs.⁸

For all the climatic variables, average data over the seasons are created, gathering the information over the months of each season. Then, climate information represents the average temperature, precipitation and relative humidity of the season, as well as the minimum and maximum temperature of the whole season.

The next figures are generated by using these interpolated variables. Due to Brazil's size, the climate varies considerably from a tropical area (northern part of the country) to temperate areas below the Tropic of Capricorn (southeastern and southern Brazil). The tropical area has higher temperatures and little variability during the year. The rainfall in Brazil has more seasonal patterns, being stronger during the summer season, from December to March (Figures 1.7 and 1.8).

⁷ The local political unit in Brazil is the municipality, which is similar to a county, except there is a single mayor and municipal council. There are no unincorporated areas in Brazil.

⁸ The interpolation technique might cause spatial autocorrelation among the errors in the regressions, however this problem is corrected by using robust estimators or bootstrapped standard errors.

Figure 1.4: Average humidity (in %) in Brazil, 2010

Source: Database from INMET. Prepared by the author.

Figure 1.5: Maximum temperature (in °C) in Brazil, 2010

Source: Database from INMET. Prepared by the author.

Figure 1.6: Average temperature (in °C) in Brazil, 2010

Source: Database from INMET. Prepared by the author.

Figure 1.7: Accumulated rainfall (in mm) in Brazil, 2010.

Source: Database from INMET. Prepared by the author.

Temperatures in Brazil are typically very high, especially in the northern regions (Figure 1.9). On the other hand, the south of Brazil has lower temperatures and occasional frosts and brief snowfalls during the winter (June to September). The northern region, which includes the Amazon Forest, is very rainy, reaching more than 3000 mm per year. The rainy season also lasts longer in this region, contrasting with the climate of the neighboring region, the Northeast, which accounts for the highest temperatures and driest seasons in the country. The semi-desert vegetation is explained by the dry climate pattern of the region.

Figure 1.8: Monthly average rainfall, in mm, 2000 to 2009

Source: Dataset from INMET. Prepared by the author.

Figure 1.9: Monthly average temperature, in °C, 2000 to 2009

Source: Dataset from INMET. Prepared by the author.

1.4 Considerations about the chapter

The evidence presented here suggests that the climate distribution might be changing over time. Such changes can be both related to the average climate modification and the climate variability/dispersion, which is expected to increase through rises in extreme events' frequency.

These changes, if confirmed, will affect many aspects of society. To identify some of these impacts, this thesis focuses on the climate effects on agricultural markets and human health (specifically dengue fever). Knowledge of the climate impacts on these aspects can serve as the basis for interventions.

The next chapter develops the study to estimate the marginal climate impacts on dengue fever incidence in the country. Both dimensions of climate are analyzed, the long-term effect, in order to identify the climate's importance on the disease's geographic distribution, and the short-term dimension, which indicates the increasing/decreasing risk of a dengue epidemics.

The following chapters present the agricultural model to detect climate influence on agricultural production and profits: Chapter 3 analyzes the average climate influence on farmers' decisions and Chapter 4 identifies the potential inefficiencies and profit decreases due to short-term climate impacts on this economic activity.

2. CLIMATE IMPACTS ON DENGUE RISK IN BRAZIL

2.1 Introduction

According to the World Health Organization (WHO, 2003), climate-sensitive health problems are one of the main public health worries of the 21st century.⁹ In the particular case of vector-borne diseases, climate conditions assure the vectors' survival and reproduction and, consequently, the transmission of the diseases.¹⁰

In Latin America the key target infectious disease is dengue fever, an emerging mosquito-borne disease that is a major public health concern in Brazil. Dengue is transmitted to humans by female *Aedes aegypti* mosquitoes, with high transmission rates throughout the day and night in urban areas. The cycle, reproduction and survival of mosquitoes are highly dependent on weather conditions. Mosquitoes depend on humid environments with temperatures in the range of 18 to 35 °C. Moreover, as mosquitoes breed in water, the accumulation of water is important for the reproduction and spread of the mosquito population (KELLY-HOPE; THOMSON, 2008).

Dengue exhibits high annual incidence (Figure 2.1 and Table 2.1). According to the Brazilian Ministry of Health's Information System for Disease Notification (MS/SINAN)¹¹, there were approximately 4.2 million dengue fever notifications in Brazil between 2001 and 2010 (Figure 2.1). In 2010, a spate of dengue fever epidemics occurred and almost one million cases of the disease were notified in the country.

⁹ The main climate-sensitive diseases are: cold-related diseases (cardiovascular and respiratory diseases); summer-related diseases (vector-borne diseases, skin diseases such as melanoma and cataracts, among others); diseases caused by extreme events, such as floods and landslides; among others (HAINES; PATZ, 2004; MCMICHAEL *et al.*, 2006; and PATZ *et al.*, 2005).

¹⁰ In the case of climate variation, the main impact on human health is related to the biology of the vectors of infectious diseases. Seasonal changes in air temperature, humidity and hydrological cycles lead to changes in the reproductive cycle and survival of these vectors, as mosquitoes have no regulatory system, their body temperature is the same as the air temperature. Thus, mosquitoes' life cycle depends strongly on the environmental conditions where they live (KELLY-HOPE; THOMSON, 2008). For this reason, vector-borne diseases are typical of tropical and poor countries, since those countries present the climate conditions for mosquitoes' survival as well as the social vulnerabilities that increase disease hazards (PATZ, 2004; MCMICHAEL *et al.*, 2006; CONFALONIERI, 2003; MENDONÇA, 2003; and PATZ *et al.* 2005).

¹¹ SINAN is a national system for notification and investigation of cases of notifiable diseases, in existence since 2001.

Figure 2.1: Dengue notifications by year in Brazil, 1986 to 2012*

Source: SINAN. Prepared by the author

* Data accumulated from January to June.

The aggravation of dengue incidence in the country caused private and public losses of about US\$ 800 million in 2010 – or US\$ 383 per hospital patient, according to Shepard *et al.* (2011). The author's calculation refers to public health expenses (hospitals and health units) and productivity losses by the families affected, not including mosquito control campaigns. When it comes to government expenses, the Brazilian Public Health System (SUS) spent on average US\$ 188 per dengue patient in 2010.¹²

Due to the growing concern with dengue and the effects of climate on this health problem, this chapter aims to understand the role of climate on the risk of dengue epidemics in Brazil. Furthermore, the incidence of infectious diseases varies in time and space, mostly due to environmental and social conditions; consequently the increase in the risk of an epidemic is also directly related to the social and physical vulnerability of the population (CONFALONIERI *et al.*, 2007). The sanitation infrastructure, for example, might be very important for amplifying or mitigating the risk of dengue. Barcellos *et al.* (2009) summarizes the multiple factors that might influence the dynamics of vector-borne diseases into subgroups: environmental factors; socio-demographic factors; medical-social factors; and local history of the disease. These subgroups will be discussed further in the next section, where the modeling strategy is explained.

¹² R\$330 converted to dollars by the 2010 average exchange rate (Source: SISBACEN PTAX800). The expenses are for hemorrhagic dengue cases and dengue fever with complications and average hospital stay of three days per patient (Source: DATASUS).

As vaccines are still not available for dengue fever, this study does not discuss vaccination programs.¹³

Brazil is an interesting setting to study the impacts of climate and public policy on the pattern of dengue, due to its regional and climatic diversity. The climate variability and dispersion among municipalities facilitates the identification of the effects of climate on dengue proposed here.

The average climate conditions of the region, as well as the short-term weather deviation from the average conditions, are analyzed in a risk function of the disease controlling for social vulnerabilities, neighborhood transmission, time dependence, and expenditures for epidemiological surveillance. Count data methods are used to assess and consistently estimate the contribution of these factors on the risk of dengue.

The first expected contribution from the measurement of these effects relates to the prevention of epidemics based on short-term climate predictions; and the second main contribution focuses on climate change and changes in population vulnerability, allowing prevention of epidemics through more appropriate long-term planning of public policies. The harmful impacts of climate change are associated not only with the increased (or reduced) incidence of the disease in endemic areas, but also with the introduction of the disease into new areas.

The following section develops the empirical strategy and the modeling approach to test the proposed problems. Section 2.3 describes the database and relevant information about the current dengue control in Brazil followed by a section that presents the outputs of the models. The final section summarizes the main findings.

¹³ The four current serotypes of dengue (DEN-1, DEN-2, DEN-3, and DEN-4) are spread in many Latin American countries, making the development of a vaccine for dengue more difficult. In spite of that, some efforts have been made in this field and local researchers believe that a vaccine will be available in Brazil between 2015 and 2017 (Folha de São Paulo, 2012).

Table 2.1: Diseases with mandatory notification in Brazil, by region of residence, 2007 to 2010.

Disease/Health Problem	Midwest	Northeast	North	Southeast	South	Total diseases, Brazil	% of total diseases, Brazil
Bites by poisonous animals	22,499	132,611	50,321	141,909	105,637	452,977	15.62%
Whooping cough	289	601	700	1,240	913	3,743	0.13%
Dengue	466,012	590,788	233,533	1,056,798	68,408	2,415,539	83.28%
Chagas disease – chronic	1	11	503	0	0	515	0.02%
Schistosomiasis	182	1,754	334	581	830	3,681	0.13%
Yellow fever, typhoid and spotted fever	41	681	400	269	114	1,505	0.05%
Hantaviruses	204	1	33	162	140	540	0.02%
Viral Hepatitis	17	30	992	78	39	1,155	0.04%
Visceral and Cutaneous Leishmaniasis	2,003	3,370	80	1,888	311	7,651	0.26%
Leptospirosis	185	2,767	1,173	1,151	5	5,281	0.18%
Malaria	596	768	312	1,816	641	4,133	0.14%
Others (botulism, diphtheria)	3	41	4	17	9	74	0.00%
Measles and rubella	1,200	1,566	469	342	197	3,774	0.13%
Total	493,232	734,988	288,853	1,206,251	177,244	2,900,568	100.00%

Source: SINAN. Prepared by the author.

Note: 1. Notified diseases by place of residence.

2. 2009 and 2010 data updated in June of 2011 and subject to revision by the Ministry of Health (MS).

2.2 Dengue risk function

The economic literature on health problems focuses on health investment and production models, starting with the seminal article by Michael Grossman (1972). The goal of this section is to formulate a model for understanding the risk of dengue in Brazil based on the ideas developed by health economics and the econometric techniques used to obtain consistent results.

2.2.1 Production function for dengue eradication

The model developed here is based on the ideas originally developed by Grossman (1972) and Corman and Grossman (1985) in studying health production functions and demand for medical goods. The motivations for individuals to pursue better health are that good health status positively affects the utility function (or sick time negatively affects the same function), and "good" health status increases the amount of hours available for work or non-work activities.

In this study, the idea of health production function is to model the risk of dengue based on determinants of the disease, which will be discussed next. The environmental influences, in particular, are considered to be exogenous to the dengue incidence or influence on dengue health status of populations:¹⁴

$$h = -d = g_1(s, m, z, c) \quad (2.1)$$

$$s = g_2(p, z, y) \quad (2.2)$$

$$m = g_3(p, z, y) \quad (2.3)$$

In which:

d denotes the incidence of dengue by number of cases;

h denotes the health status related to dengue incidence (the higher the incidence of dengue, the lower the value of the variable h);

s denotes the variables that measure the urban infrastructure of the site (primarily sanitation: water, sewage and garbage collection coverage, considered as inputs);

c denotes exogenous variables related to environment (climate, among others);

m represents medical supplies (public investments to control zoonosis, for example);

¹⁴ Dengue is influenced by environmental conditions, but environment is not influenced by dengue cases.

p denotes variables related to prices and available measures for inputs considered (s and m);

z denotes other exogenous risks and productivity factors for the lower incidence of dengue fever (urbanization, proximity to border/coastal areas);

and y represents the socioeconomic characteristics that are important vulnerability indicators of the disease (income, education, inequality).

Thus, the function g_1 is a production function that presumes that individuals can influence their health status. The function captures the relationship between health inputs and other exogenous factors and health status while g_2 and g_3 are equations of derived demand for inputs in the study¹⁵. Replacing the derived demands in the health production function for dengue yields:

$$h = -d = g_1(p, y, z, c) \quad (2.4)$$

$$d = -g_1(p, y, z, c) \quad (2.4')$$

Equation 2.4' is estimated using data from Brazilian municipalities, the incidence of dengue depends on local environmental conditions, as well as actions to control the disease, such as local infrastructure and other socioeconomic characteristics.¹⁶

After accounting for the all the determinants of dengue, the final model is a reduced form and can be described by:

$$d_i = g(d_i^{t-1}, d_i^j, M_i, E_i, C_i, F_i, S_i, P_i, V_i, pd_i), \forall i, j = 1, \dots, N \text{ and } i \neq j \quad (2.5)$$

The above equation can be interpreted as a risk function for dengue (d). Detailed information about the function arguments is given in the next section. The function can be estimated by using statistical and mathematical formulations for count data models (LOWE *et al.*, 2010; PATZ *et al.*, 1998).¹⁷

¹⁵ To support these equations, it is assumed that individuals consider dengue eradication as a normal good, which brings welfare to the family.

¹⁶ A major problem related to estimation is possible endogeneity in equation 2.4' due to the reverse causality measure of public investment for dengue control, which will be further discussed as an econometric problem.

¹⁷ Ecological studies for dengue normally investigate the effect of the evolution of the mosquito on the incidence of the disease, disregarding factors not closely related to reproduction and development of mosquitoes, such as regional and socioeconomic factors, which are important for disease vulnerability (HALES *et al.*, 2002; WU *et al.*, 2009).

2.2.2 Dengue risk determinants

The determinants of dengue incidence can be subdivided into four groups: environmental, socio-demographic and medical factors and local history of the disease (BARCELLOS *et al.*, 2009).

The environmental factors are strongly dominated by the importance of climate (C) on the incidence of dengue, as outlined in the introductory section. The relevant climate conditions for the dengue vector's survival and reproduction are: average temperature not too low or high, sufficient humidity to regulate the temperature of mosquitoes, and a reasonable amount of precipitation for the deposition of eggs. Regarding the amount of rainfall, it is believed that large amounts of rain may have the reverse effect, since this can wash away standing water accumulations, reducing the number of larvae.¹⁸

Furthermore, vegetation (V) might be relevant to guarantee water accumulation. Thus, it is important to consider the change in vegetation across the regions analyzed as an important risk factor for communities, especially in rural areas. However, the green areas must be close to populations in order to present additional risks of transmission.

When it comes to socio-demographic factors, four of them are important to study the incidence of dengue: urbanization or population density (pd); income¹⁹ and education (average income, P , and educational level, E), coverage of water, sewage and garbage collection systems (S); and other information on susceptible areas (F).

Urbanization and population density might be important accelerators of dengue transmission. In the case of sanitation information, lack of water and sewer system and garbage collection services in some regions of the country, mainly poor areas, forces some families to keep reservoirs of drinking water. These reservoirs, largely with irregular maintenance, act as breeding places of mosquito larvae.

In regard to other susceptible areas (F), border areas and coastal regions can also influence the dengue distribution: coastal location might play a role because of the natural increased humidity in those areas; on the other hand border regions are more sensitive to dengue due to the dengue transmission from other countries, especially Bolivia, Venezuela and Colombia (MACIEL *et al.*, 2008).

¹⁸ Due to these arguments, climate might have a non-linear relationship with the incidence of the disease.

¹⁹ Income might influence the environmental consciousness of people, but this effect is assumed to be small in this analysis.

The incidence of dengue is also influenced by educational level of the population (E), serving as an important component of the hazard function of dengue.²⁰ Part of the literature relating health and education suggests that education acts through the better use of other determinants of dengue (GROSSMAN; KAESTNER, 1997). In other words, in cities with more educated people, there is better use of inputs for eradication of dengue. Possible causal relationships between education and health, reported in the literature, are excluded from this analysis, since they do not make sense in the context of the study of dengue.²¹

To test for the local history of the disease, a dynamic component is defined (d^{t-1}). The dynamic component measures the influence of the previous notifications of dengue, which might help to explain important situations not observed, such as immune status of the population and prevalent serotypes, among others. Furthermore, it allows checking the time dependency of the disease. The spatiality of the transmission must be accounted for as a proxy for spatial contagion from dengue transmission in the neighborhood (j municipalities), d^j (WEN *et al.*, 2006). Both measures might generate endogeneity in the model, which will be further discussed.

The influence of public health investment in inputs for the eradication of dengue fever and other zoonosis (M) is also an important determinant to test in the model. In the specific case of Brazil, the dengue control programs are discussed in Section 2.3.3 and their effectiveness in dengue mitigation in the country is tested. The following sections investigate the econometric treatment of the dengue risk equation and the potential endogeneity from the medical variables.

2.2.3 Econometric approach: Count data model

The dengue variable is measured as the number of notifications per municipality and information over the previous years is also observed. Due to the nonnegative and discrete data generating process of the dependent variable of interest, *dengue cases* [d_i], its distribution places probability mass at nonnegative integer values only. The most common distributions for count data distributions are the Poisson and negative binomial

²⁰ The literature that bases this argument suggests that education has important impacts on health and diseases incidence (GROSSMAN, 1972; CROPPER, 1981; NOVI, 2007).

²¹ There is a discussion over the causality of schooling based on the time preference hypothesis (FUCHS, 1982). People who are more future-oriented tend to have a higher degree of time preference for the future, attend school for longer periods of time and make larger investments in health. Thus, the effect of schooling on health might be biased if one fails to control for time preference.

(HAUSMAN *et al.*, 1984; DEGROOT; SCHERVISH, 2002; CAMERON; TRIVEDI, 2010).²²

According to Cameron and Trivedi (2010), the standard complications from count data models include: (i) small-mean property of the dependent variable, caused by the excess of zeros; (ii) endogenous regressors; (iii) overdispersion of the data (cases when conditional variance is higher than conditional mean)²³.

In order to understand the presence of these complications and treat them properly, a series of models are estimated, based on both distributions, using maximum likelihood.

The modeling strategy is to present the base-model (Poisson model) in order to assume different hypotheses about this model and generalize the results in light of the mentioned complications.

(a) Poisson model

This model assumes that the dependent variable (d), which is a random variable, follows a Poisson distribution²⁴, $d \sim \text{Poisson}(\mu)$, such that:

$$E(d) = \text{Var}(d) = \mu \text{ and } \mu = \exp(z'\beta) \quad (2.6)$$

In which: z is the matrix of covariates and β is the $K \times 1$ vector of parameters.

The Poisson maximum-likelihood estimator (MLE) is the solution of K nonlinear equations corresponding to the maximum-likelihood (ML) first-order conditions. The Poisson MLE is consistent even when the distribution is not a Poisson, but the conditional mean specified above is correct (CAMERON; TRIVEDI, 2010).

Robust estimates of the variance-covariance matrix control the problem (iii) of overdispersion, which can be tested by the model and imposed to obtain consistent standard errors.²⁵

Like all nonlinear models, the Poisson MLE estimates can be analyzed by generating the marginal effects evaluated at specific values.

²² These distributions consider the data generating process on the number of random events in a fixed period of time and number of trials needed for a particular event.

²³ Overdispersion is more common than underdispersion in applied works.

²⁴ $P(d = d_i) = \frac{e^{-\mu_i} \mu_i^{d_i}}{d_i!}$ is the Poisson probability mass function of d .

²⁵ As demonstrated by Cameron and Trivedi (2010), a quasi-maximum likelihood approach can be used to consistently estimate the variance-covariance matrix (VC). However, a bootstrap procedure can also be used to generate robust estimators for the VC matrix.

(b) Negative binomial model (NB)

This model accounts for overdispersion from the presence of unobserved heterogeneity (v) by modeling both d and the potential heterogeneity that causes overdispersion: $d \sim \text{Poisson}(\mu v)$; in which $\mu = \exp(z'\beta)$.

For a Gamma distribution for v^{26} , with mean 1 and variance α , the overdispersion model is derived and α represents the size of the overdispersion. Thus, $d \sim \text{NB}(\mu, \alpha)$ and this negative binomial model explicitly models overdispersion, allowing hypothesis testing on its size (α). The moments of the variable are: $E(d/\mu, \alpha) = \mu$ and $\text{Var}(d/\mu, \alpha) = \mu(1 + \alpha\mu)$.

Cameron and Trivedi (2010) highlight that the negative binomial MLE is not consistent when its variance specification is incorrect. However, the quadratic form is considered a good approximation of general variance functions. The NB is preferred in the presence of overdispersion when the objective is to model the probability distribution in addition to the conditional mean. This model is also estimated by ML.

(c) Hurdle model

This model relaxes the assumption that the zeros and the positive integers of the dependent variable come from the same data generating process, assuming a different distribution of the zero probability and of the positive probabilities (truncated at zero).

The model is implemented in two-steps by ML (CAMERON; TRIVEDI, 2010):

- I) Estimate the parameters of a binary outcome model (logit/probit/linear probability);
- II) Estimate the parameters of the count data model truncated at zero.

Thus, it is possible to obtain different effects from the zero modeling and from the positive outcomes modeling.

By using the three models specified, the specification can be tested. The high number of zeros problem (i) can also be controlled by the hurdle model, which estimates separately the zeros and the positive values of the dependent variable.

The only problem not accounted for those models is the potential endogeneity of the regressors. In order to attack this problem, instruments for the endogenous variables are

²⁶ The Gamma distribution generates tractable solutions.

necessary to identify the model and consistently estimate the intended effects. Once the instruments are observed (exogenous instrumental variables strongly correlated with the instrumented variable), reduced form equations can be estimated and their residuals included in the structural model, estimated by ML. If the residual coefficients are statistically significant (indicating correction of endogeneity), standard errors should be obtained by bootstrap (CAMERON; TRIVEDI, 2010).

The following subsection discusses the variables that are potentially endogenous in the model and the necessary identification hypothesis to consistently estimate the dengue risk function.

2.2.4 Problems concerning endogeneity

The three main sources of endogeneity come from: (a) the time lagged dengue incidence; (b) the spatial lagged dengue variable; and (c) local government expenditures for dengue control.

(a) Dynamic component (time lag for dengue):

The dynamic component of dengue transmission is included to test the relevance of local history on dengue incidence. One way to consider this behavior in the model is to include a lagged dependent variable for municipality i (d_i^{t-1}) as a covariate, as equation 2.5 shows.

There are two main reasons for the correlation of d_i^t and d_i^{t-1} in cross-sectional models: the existence of *true state dependence*, which may account for historical factors that cause differences in dependent variables (inertial or immunological effects); and *non-observed heterogeneities*, which can be captured by the previous information on the disease.

The estimation of models with lagged dependent variable as covariates leads to inconsistent parameter estimates (CAMERON; TRIVEDI, 2010). However, when higher lags of the variable are available ($d_i^{t-q}, q > 1$), they can be used as natural instruments for the endogenous variable. Formally, the reduced form equation estimated is:

$$d_i^{t-1} = \theta_0 + \sum_{q>1} \theta_q d_i^{t-q} + \delta x_i + res_{1i} \quad (2.7)$$

In which $\mathbf{x}$ represents the matrix of exogenous regressors from the structural equation 2.5, and δ 's and θ 's are parameters to be estimated.

(b) Spatial lag component (spatial lag for dengue):

The spatial lag model must be used when there is suspicion of spatial contagion in the modeling approach. The existence of spatiality is based on the First Law of Geography: “Everything is related with everything else, but closer things are more related.” (TOBLER, 1970). The theoretical idea involving the inclusion of a spatially lagged dependent variable (d_i^j) is that this might capture the contagious effect in i from dengue transmission in its neighborhood j .

Cliff and Ord (1973, 1981) developed statistical models which accommodate explicit forms of cross-sectional interactions based on geographic-science models. Following Cliff and Ord (1973, 1981), the spatial literature was developed to handle spatial interactions. The basic topology of the spatial system is captured by a weighting matrix $\mathbf{W}$, exogenously determined, which applies specific weights for each neighbor of the spatial unit of analysis. Therefore, the spatial lag component can be described as:

$$d_i^j = \sum_{j \neq i}^n w_{ij} d_j \quad (2.8)$$

In matrix form:

$$\mathbf{d}^j = \mathbf{W} \mathbf{d} \quad (2.8')$$

In which:

$$\mathbf{W}_{n \times n} = \begin{bmatrix} 0 & w_{12} & \dots & w_{1,n-1} & w_{1n} \\ w_{21} & 0 & \dots & w_{2,n-1} & w_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ w_{n-1,1} & w_{n-1,2} & \dots & 0 & w_{n-1,n} \\ w_{n1} & w_{n2} & \dots & w_{n,n-1} & 0 \end{bmatrix} \quad (2.9)$$

As Lambert *et al.* (2010) highlight, the theory and application of spatial econometrics in discrete dependent variable settings is less developed when compared to the linear cross-sectional and panel data models²⁷. Their paper is the first in the spatial

²⁷ There are some previous works by Kaiser and Cressie (1997) using count model and a type of spatial dependence, or the work of Rasmussen (2004) specifying a model based on the generalized linear mixed model (GLMM) and on conditional autoregressive models incorporating neighborhood contiguity into the coefficients. Most of this recent literature, which deals with count data and spatial relations, not only does not clearly address the global spatial dependence of cross-sectional units, but also does not treat the endogeneity intrinsic to the inclusion of a spatial dependent covariate. Furthermore, this literature only

econometric literature to address the problem of estimating a spatial lag model from a count data distributed variable with endogeneity.

They propose a two-step procedure similar to that described in (a) for endogenous variable treatment in those models. The only difference is that they use a variance-covariance adjustment instead of generating standard errors by bootstrap. The set of instrumental variables used is typical of spatial lag variables: suppose that $[x]$ is the exogenous vector for the independent variables; thus, the instruments for Wd are the spatially lagged exogenous variables (Wx and WWx).

Formally, the reduced form equation estimated is:

$$d_i^j = \theta_0 + \theta Wx_i + \rho WWx_i + \delta x_i + res_{2i} \quad (2.10)$$

In which x represents the matrix of exogenous regressors from the structural equation and δ 's, ρ 's and θ 's are parameters to be estimated.

(c) Local health expenditures/interventions:

Apart from the natural endogeneity from dynamic and spatial components, the main observed endogeneity in the dengue risk function is due to reverse causality of public investments in actions for dengue control.

The expenditures for epidemiological surveillance in Brazil are normally made by observing epidemics in the beginning of the year (see Section 2.3.3). Thus, more dengue cases also imply higher expenditures for epidemiological surveillance. In order to control for this reverse causality, instruments are used. In this case, local government expenditures for epidemiological surveillance on the previous years are tested, and used, as instruments to correct for endogeneity biases caused by the reverse causality problem.

The endogeneity treatment follows the procedure to include the endogenous residual from the reduced form equation (endogenous against instruments and other exogenous variables of the model) in the structural equation and to generate the standard errors by bootstrap, as the residual component prevents the robust calculation of the VC matrix. Formally, the reduced form equation estimated is:

$$M_i = \theta_0 + \sum_{q \geq 1} \theta_q M_i^{t-q} + \delta x_i + res_{3i} \quad (2.11)$$

models the dependent variable and does not worry about other important determinants of the object analyzed.

In which $\mathbf{x}$ represents the matrix of exogenous regressors from the structural equation and δ 's and θ 's are parameters to be estimated.

2.2.5 Stages of estimation

All in all, the count data model with endogeneity correction can consistently estimate the effects of the determinants on dengue risk. Formally, the dengue risk equation estimated is:

$$E(d/\mathbf{x}_i) = \exp(d_i^{t-1}, d_i^j, \mathbf{M}_i, \mathbf{E}_i, q(\mathbf{C}_i), \mathbf{F}_i, \mathbf{S}_i, \mathbf{P}_i, \mathbf{V}_i, \mathbf{res}_i); i = 1, \dots, n; t = 2010 \quad (2.12)$$

In which:

$\mathbf{res}_i = (res_{1i}, res_{2i}, res_{3i})$: indicate the error components estimated from each of the reduced form equations of the endogenous variables against the exogenous equation plus its instruments (from equations 2.7, 2.10 and 2.11);

$\mathbf{x}_i$ is the vector of exogenous covariates of the model.

Note that a polynomial specification of climate is assumed, $q(\cdot)$, to test nonlinearities in the relationship between climate conditions and dengue incidence. Equation 2.12 is estimated by the following methods:

- (1) Poisson model;
- (2) Negative binomial model; and
- (3) Hurdle model.

The analysis of the results is based on the following steps:

- I) Test whether climatic variables, both in short- and long-term, impact the incidence of dengue in Brazil;
- II) If the hypothesis that average climate impacts dengue incidence is not rejected by the data, it is possible to predict the expected effect of climate change on the geographic distribution of dengue; and
- III) Once the hypothesis that deviations from the average climate (short-term climate) impact on dengue incidence is tested, it is possible to illustrate new ways to monitor dengue cases in the short-term.

2.3 Data sources and description

This section discusses the sources of data used for the estimations, as well as shows some evidence regarding the spatial distribution of dengue in Brazil and its relationship with climate distribution. The end of this section shows the main actions to combat dengue in the country since the 1990s.

2.3.1 Data sources

The data on dengue notifications are at the municipal level, collected by the SINAN, which contains all notified cases of dengue in the year by municipality of residence reported.²⁸ Municipalities are the smallest administrative unit in Brazil. These reports include cases of dengue fever and dengue hemorrhagic fever.

The period analyzed is 2010, when an outbreak of several regional dengue epidemics occurred, but historical information is also collected to control for the potential endogeneities mentioned. The year 2010 was chosen based on the availability of the Demographic Census for this year, conducted by the Brazilian Institute of Geography and Statistics (IBGE). The operationalization of the SINAN was defined by Edicts 1,399 (BRAZIL, 1999) and 95 (BRAZIL, 2001). Therefore, the data for 2000 were not available to allow for panel data analysis using the two latest population censuses.

The climate information is collected by INMET and described at Chapter 1. The information collected for this study is average temperature, relative humidity and rainfall. For all the climatic variables, average data over the seasons are created. The variables are subdivided into two groups:

- *Average climate conditions (long-term climate variable), $E(C_{1980-2009})$* : Pattern of rainfall, air temperature and relative humidity by season from 1980 to 2009 (long-term average); and

²⁸ Dengue notifications might deviate from actual dengue cases due to unreported cases (incorrectly diagnosed or not diagnosed). The measurement error generates a consistency problem only if this error is correlated with the independent variables, violating the exogeneity assumption (GREENE, 2003). It is assumed that only the mean of the average error is different from zero, influencing the bias of only the constant parameter estimated, but it is uncorrelated with the covariates, generating consistent estimators for the other coefficients. The inference problem from the positive VC matrix of the measurement errors is naturally treated by generating standard errors from a bootstrap procedure.

- *Deviation from climate conditions (short-term climate variable)*, $C_{2010} - E(C_{1980-2009})$: Deviations from the pattern of rainfall, air temperatures and relative humidity by season in 2010.

For climate predictions, CPTEC/INPE data are used. The CPTEC model for climate change forecasts is described in Chapter 1.

When it comes to the social and demographic variables, most of them are available from the last Brazilian Demographic Census, 2010. The variables included and tested in the dengue risk model are subdivided into categories and described below. Only a few of those variables are collected from different data sources. When this is the case, the source is identified in parentheses right after the variable explanation:

- *Educational variables*: Illiteracy rate; percentage of people from different educational levels, measured by years of schooling (0 to 8 years; 9 to 12 years; 13 years; 13 to 17 years; more than 17 years).
- *Regional variables*: Area in square kilometers of the municipality; dummies for border and coastal municipalities (IBGE).
- *Demographic variables*: Population density, population per square kilometer (IBGE); percentage of urban households; total population.
- *Income/Social variables*: Median income for rural and urban households; percentage of people from each income level, in multiples of the minimum monthly wage²⁹ - MW (no income; 0 to 0.25; 0.25 to 0.5; 0.5 to 1; 1 to 2; 2 to 3; 3 to 5; 5 to 10; 10 to 15; 15 to 20; 20 to 30; more than 30 MW); ownership of durable goods (radio, TV³⁰, computer, internet modem, and vehicle); percentage of households with at least one bathroom; wall construction material (concrete, wood, others).
- *Urban infrastructure*: Garbage collection; sewer system; water system.
- *Health inputs*: Local authorities' total expenses on individual health, family health and epidemiological surveillance per person (Finbra³¹ database from 2005 to 2010)³²; percentage of households in the municipality receiving assistance from the

²⁹ The minimum monthly wage in Brazil was R\$ 510 in 2010, or about US\$ 290.

³⁰ The variable on the inclusion of televisions and radios in the municipalities analyzed seeks to measure the possible effect of advertisements and actions of the government against dengue in the period.

³¹ Finbra is the report of the information about income and expenses of each Brazilian municipality, released by the National Treasury of Brazil.

³² According to the Edict 1399 (BRAZIL, 1999), the epidemiological surveillance expenditures by municipality might comprise the following activities: notification of reportable diseases; epidemiological

Family Health Program (PSF) in 2010 (Datasus); number of visits per family assisted (PACS or PSF); number of private and public hospitals in the municipality (Datasus).

- *Other environmental variables*: Normalized Differenced Vegetation Index, NDVI (NASA and Data Library)³³; dummies for Brazilian biomes (IBGE).³⁴

As for the spatial variable, which potentially measures the neighborhood contagion, two different weighting matrices are tested to identify the spatial dependence structure of dengue: queen contiguity of first order; and distance matrix of 250 kilometers. The OpenGeoda software is used to generate the matrices for neighborhood (ANSELIN *et al.*, 2005): All weights of $\mathbf{W} = [w_{ij}]$ are calculated as inverse distance from neighbors and standardized so that each row sums to unity (1): $w_{ij}^* = \frac{1}{d_{ij}}$; $w_{ij} = \frac{w_{ij}^*}{\sum_j w_{ij}^*}$ ³⁵.

The two matrices presented similar results for the spatial lag coefficients, so the queen contiguity matrix is used for the further calculations due to its simplicity.

2.3.2 Description of the variables

(a) Dengue incidence and climate

In Brazil, the number of dengue cases has been increasing in recent years (see Figure 2.1, Section 2.1), suggesting some state dependence of the aggregate data, with small epidemics during the 1990s and higher incidence from 2002 on.³⁶

The Southeast and Midwest suffered the highest incidence of dengue in 2010, accounting 458,515 cases and 209,855 thousand cases respectively. The incidence in the Northeast reached 166,048 cases and in the North 95,687 cases (when relativized by the population, these figures are similar to the Southeast number of infected per

investigation; capture of vectors; identification and collection of the rate of infestation; actions of chemical and biological control of vectors and eliminating breeding sites, among others.

³³ NDVI is an indicator which represents the probability of having vegetation by remote sensing measurements (live green vegetation or not). It varies from -1 to 1.

³⁴ See Appendix A.2.4 for the description of biomes in Brazil.

³⁵ For the queen contiguity matrix, all the neighbors receive the same weights.

³⁶ Braga and Valle (2007) comment on the epidemic cycles of dengue in Brazil: the first from 1986 to 1987 showed a small increase in incidence of the disease; the second in 1990 and 1991 mainly affected the states of Ceará and Rio de Janeiro; the third in 1994 involved the whole country, after which dengue cases increased again from 1997 to 1998. A forth epidemic cycle began in the 2000s and was not covered by the authors.

population). The South region (more temperate climate) had a low number of cases in 2010 compared to other regions (37,823).³⁷

Table 2.2: Distribution of dengue cases by region, Brazil, 2010.

Region	Number of notifications (2010)	Notifications per population*
<i>Midwest</i>	209,855	1.49%
<i>Northeast</i>	166,048	0.31%
<i>North</i>	95,687	0.60%
<i>Southeast</i>	458,515	0.57%
<i>South</i>	37,823	0.14%
Brazil	967,928	0.51%

Source: Population information: Demographic Census 2010; Dengue data: MS, SINAN. Consulted in February, 2012. Prepared by the author.

The following figure shows the spatial distribution of notifications during the 2010 epidemics and illustrates the high incidence all over the country, except for the South, where the climate conditions are less favorable for mosquitoes.

Figure 2.2: Spatial distribution of dengue notifications per 100 thousand inhabitants, Brazilian municipalities, 2010.

Source: SINAN. Prepared by the author.

³⁷ Figure A.2.4 in Appendix A.2.1 shows the percentage of municipalities of the states where there were at least one dengue case during 2010. The states of the South of Brazil and some specific states in the North of the country (Amazonas, Piauí and Maranhão) are less susceptible to dengue. When it comes to the southern states, the above evidence suggests that climate conditions are an important factor that contributes to the absence of the disease in this region, because the average climate conditions are not favorable to the survival of mosquitoes. Regarding the state of Amazonas, the high rainfall and the dense forest can explain the low number of dengue cases in the state. Extremely high rainfall, for example, normally washes away the mosquito larvae, reducing the vector population.

The figures in Appendix A.2.1 show the seasonal average distribution of rainfall and temperature for biomes in Brazil, briefly summarized in Table 2.3.

Table 2.3: Average climate conditions by biomes and season, long-term average from 1980 to 2009.

Climate by biome	Amazônia	Caatinga	Cerrado	Mata Atlântica	Pampa	Pantanal	Average (Brazil)
<i>Rainfall monthly average from 1980-2009, in millimeters (mm)</i>							
Summer	216.3	97.1	213.2	175.4	146.3	213.2	171.5
Fall	243.9	141.1	140.5	111.9	101.3	136.0	132.4
Winter	89.1	54.7	26.1	68.1	92.2	45.6	60.1
Spring	95.2	28.2	99.2	114.9	135.0	118.8	95.7
<i>Temperature monthly average from 1980-2009, in °C</i>							
Summer	26.3	26.3	24.9	23.7	23.0	25.6	24.6
Fall	26.0	25.5	24.1	21.6	19.4	24.2	23.0
Winter	25.8	24.3	22.5	18.0	14.0	21.8	20.5
Spring	27.0	26.4	25.1	21.5	18.4	25.0	23.4
<i>Relative humidity monthly average from 1980-2009, in %</i>							
Summer	84.0	69.9	78.5	76.5	74.7	82.6	76.3
Fall	85.1	76.5	77.3	77.6	77.5	81.9	77.9
Winter	75.9	69.8	64.8	73.8	75.9	72.9	71.6
Spring	75.2	62.6	66.5	72.0	74.0	74.4	69.6

The table shows evidence of the tropical features of the Amazon region (in the North region), with high temperatures year-round, and more temperate areas in the Pampa and Mata Atlântica biomes, representing most of the southern and southeastern regions of Brazil.

Precipitation in Brazil has a strong seasonal component, being more intense during the summer and fall. The rainiest biomes are Amazonia, Cerrado and Mata Atlântica, respectively. The Pampa, in the South of Brazil, has lower temperatures with occasional occurrence of frosts during the winter, decreasing the probability of mosquito survival in the region. In the case of the Caatinga, low rainfall during most of the year causes poor conditions for mosquitoes to breed.

(b) Explanatory variables

The completed table of the descriptive statistics of the explanatory variables is available in Appendix A.2.2 due to its size. The evidence extracted from the table is discussed here. The information is basically an overview of the municipal data from the latest census and other sources.

Urban households represent most of the population of nearly all municipalities. Approximately 11% of the municipalities are located along the border of the country and 7% of municipalities are on the coast.

On average, the majority of the people has no education or did not complete elementary school (0 to 7 years of schooling). Illiteracy rates seem to give more information on educational standards for the municipalities. On average, the municipalities have 14% of illiterate people and approximately 59% of those municipalities have higher illiteracy rates than the Brazilian average of 10%. The average for men is higher than for women.

When it comes to income levels, the municipalities have on average more people in the ranges from 0.5 to 2 times the MW. Fewer people received more than 10 times the MW in 2010. On average, the non-labor income percentage of the municipalities is high, suggesting that many households do not have a single main income provider. Another informative source for income is the median per household income of the municipality, which varies from R\$ 134 (or US\$ 76, lower than the MW) to R\$ 3000 (US\$ 1704). The median income for the urban population is about US\$ 114³⁸ higher than the median income of the rural population. The Gini coefficient calculated measures the inequality among values of the frequency distribution of labor income using 2010 data. The Brazilian average is 0.46 and varies from 0.23 (most equal municipality) to 0.78 (most unequal municipality).

According to the census, the majority of municipalities, on average, have households that own radios and televisions and few families have computers (and Internet access). Normally, ownership of durable goods is an indicator of income. However, in the context of dengue, the ownership of radios and televisions might also measure how informed people are by the media. During dengue epidemics, the federal government typically uses the media not only to alert people about the disease, but also to educate communities regarding precautions to reduce mosquito breeding places.

When it comes to vehicle ownership, there is a lot of variation among municipalities, but the average analysis indicates that ownership of cars is more common than motorcycles in the majority of municipalities.

The average of the municipalities that have some waste disposal is 70% (collected or burned). Garbage disposed in no specific location accounts for 5 to 6% of the

³⁸ Converted to dollars by the 2010 average exchange rate. Source: Sisbacen PTAX800.

municipalities. The access to a public sewage system is, on average, very poor among the municipalities and seems to be unequally distributed. Rudimentary cesspits are more common than integrated networks. There are still a significant proportion of municipalities with high rates of raw sewage discharge into rivers, lakes, sea or ditches. Water supply is more equally distributed in the country. However, 11.4% of the municipalities, on average, still do not have access to piped water.

The most important results regarding climate variables is that 2010 was a year of higher than normal air temperatures (when compared to the long-term averages) in all seasons. In terms of humidity, the year in general was less humid in most municipalities. The rainfall comparison between 2010 and the long-term average showed less rainfall in many areas (Minas Gerais, Espírito Santo, Bahia, and northern part of Northeast region). The climate deviations are mapped and are exhibited in Appendix A.2.3.

The descriptive analysis of the health data shows there are more public hospitals than private ones in Brazilian municipalities, on average. When it comes to the families assisted by the PSF, there are municipalities fully assisted and municipalities no assisted by the program. On average, 18% of municipalities nationwide participate in the program. The average number of household visits by PSF agents is eight per year.

The analysis of the average health expenditures per person shows an increase from 2005 to 2010. As for the epidemiological surveillance spending, it is still low at R\$ 4.70 (US\$ 2.83) per inhabitant in 2010. More money is spent for basic health assistance (as the PSF), which represented about R\$ 227 (US\$ 136.3) per inhabitant in 2010.³⁹ In the next subsection the current government actions to reduce dengue epidemics in Brazil are discussed.

2.3.3 Current dengue control in Brazil

According to the Ministry of Health, the socio-environmental conditions in most of Brazil are favorable to the development of *Aedes aegypti*. Therefore, the environmental conditions have permitted the dispersion of the vector and increase of dengue during recent years (MS, 2011). Serotype 2 (namely DEN2) was responsible for the increase in the disease in the 1990s and the third serotype appeared in 2001 in Rio de Janeiro and is

³⁹ Converted to dollars by the 2010 average exchange rate. Source: Sisbacen PTAX800.

currently observed in 25 out of the 27 Brazilian states, according to Braga and Valle (2007).

During the 1990s, dengue control was established by zoonosis control. The Ministry of Health invested about US\$776 million⁴⁰ at the time in staff, vehicles and surveillance equipment. However, the action was not successful in achieving the targeted reduction of dengue (BRAGA; VALLE, 2007). These results prompted the Ministry of Health to implement the National Dengue Control Program (PNCD) in 2002 (MS, 2011), whose proposal for dengue control relies primarily on the collective action of society as a whole. The PNCD also included the mobilization of the health agents of the PSF (Family Health Program) in dengue control.⁴¹

Among the duties of the municipal program, the role of public education and chemical and biological control of mosquitoes can be highlighted. The Ministry of Health invested US\$ 300 million in the PNCD in 2002⁴², 85% of which went for surveillance and vector control. The following year, the actions absorbed about US\$ 274 million⁴³ (BRAGA; VALLE, 2007). The program has not achieved the goals of eradicating dengue.

Lowe *et al.* (2010) highlighted that the current system of monitoring dengue in Brazil is based on the observation of dengue cases in January and February, with occasional interventions by spraying insecticides to kill mosquitoes and their larvae where an increase in the number of cases is detected. This monitoring system is more corrective than preventive, not using a forecasting mechanism that could anticipate the occurrence of epidemics.

Some studies, such as Thomson *et al.* (2006) and Kuhn *et al.* (2005), argue that in places where infectious diseases are not adequately controlled, weather information is relevant to know the seasonality of endemic diseases, changes in the spatial distribution of diseases and changes in risk of epidemics through early warning systems. Nowadays, there is still no single technique for eradication of the mosquito.

⁴⁰ R\$ 1 billion converted to dollars by the average exchange between 1995 and 1999. Source: Sisbacen PTAX800.

⁴¹ The components of the program were: epidemiological surveillance; vector control; inpatient assistance; basic assistance integration (PACS and PSF); environmental sanitation actions; integrated health education actions, communication and social mobilization; training of human resources; legislation; political and social support; monitoring and evaluation of PNCD plan.

⁴² RS 1.04 billion converted to dollars by the average exchange rate in 2002. Source: Sisbacen PTAX800.

⁴³ RS 0.79 billion converted to dollars by the average exchange rate in 2003. Source: Sisbacen PTAX800.

2.4 Results

This section presents the main results of each stages of estimation. In summary, the analysis of the dengue risk function is based on the following steps:

- Step I: Estimation of the dengue risk equation and testing whether climate variables impact the incidence of dengue in Brazil;
- Step II: If the average climate impact on dengue incidence is statistically significant, it is possible to predict the expected effect of climate change on the geographic distribution of dengue;
- Step III: Once the deviation from the average climate impact on dengue incidence is tested, it is possible to illustrate new ways to monitor dengue cases in the short-term.

As mentioned, climate variables are included in polynomial form (3rd order) in order to control possible nonlinearities. The total number of Brazilian municipalities in the sample is 5,564 and the models are estimated considering instruments for the potential endogenous variables discussed in Section 2.2.4 and bootstrapped standard errors after 1,000 replications. The dengue risk equation is estimated using Stata 11.1 SE.

2.4.1 Step I: Climate relevance

The first step is to test the significance of climate variables in explaining dengue incidence. Table 2.4 shows the joint tests for the climate variables and other important groups of variables, such as health input covariates:

Table 2.4: Joint test for the covariates, models (1) to (3), 2010.

Variables tested	(1)	(2)	(3)
Average climate: $E(C_{1980-2009})$	48.09***	553.52***	338.88***
Short-term climate: $C_{2010} - E(C_{1980-2009})$	32.23***	76.54***	48.29***
All climate variables above	72.12***	696.31***	430.19***
Health input variables [#]	45.27***	30.56***	29.32***
Income variables ^{##}	27.16***	18.43**	10.24*
Sanitation variables ^{###}	5.86	15.21***	10.20**

(1) Poisson; (2) Negative Binomial; (3) Hurdle; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[#] Family Health Program variables, expenditures on basic health, expenditures on epidemiological surveillance; ^{##} median income, Gini coefficient, dummies for ownership of durable goods; ^{###} water, sewage and waste disposal coverage.

The F-test for the joint significance of the long-term climate variables indicates they are relevant to explain dengue risk in 2010 for Brazilian municipalities in all equations. The

same tests for the climate variability variables suggest the relevance of the short-term climate conditions for the disease risk. Other groups of variables that represent income, sanitation conditions and health inputs in the municipality are also relevant for explaining dengue, as the joint test indicates.

The following tables and figures exhibit the marginal effects for these variables in each of the models estimated, calculated from the sample average.

Table 2.5: Marginal effects from models (1) to (3), 2010.

Variables	(1) Poisson	(2) Negative Binomial	(3) Hurdle
Spatial lag for dengue 2010	0.00944**	0.0181***	0.0326***
Time lag for dengue in 2009	0.000873	-0.000202	0.00298
Dummy for Amazon region	4,835	1,280**	31.82
Dummy for Caatinga region	1052*	681.1***	1.625
Dummy for Cerrado region	2130*	611.3***	5.151
Dummy for Mata Atlântica region	221.2***	92.72***	-31.20*
Dummy for Pampa region	Base dummy	Base dummy	-63.26***
Dummy for Pantanal region	4,825	1,058	Base dummy
Illiteracy rate	0.190	0.0349	0.350
Median income	-0.00420	8.34e-05	0.00178
Gini coefficient	94.66***	26.28**	51.51
% of households: ownership of radio	-0.619***	-0.151**	-0.176
% of households: ownership of TV	0.0817	-0.443***	-1.198***
Coverage of water system	0.148	0.123**	0.284*
Coverage of sewage: system and septic tanks	0.0453	0.130	-0.441
Precarious conditions of sewage	0.104	0.179	-0.270
Precarious conditions of waste disposal	-0.687*	-0.304*	-0.899*
% of urban households	43.73***	31.28***	65.87***
% of people from 0 to 9 years	-2.174	-0.318	3.543
% of people from 10 to 19 years	-0.0868	1.729*	7.737**
% of people from 20 to 29 years	-1.822	0.357	3.179
% of people from 30 to 49 years	0.348	1.968**	7.912***
% of people from 50 to 69 years	-0.497	1.146	9.588**
Vegetation index (NDVI) - 2006	-33.01*	-25.01**	-79.75**
Dummy for border municipalities	42.10***	26.76***	93.16***
Number of public hospitals	-0.498	-0.556	-1.766
Number of private hospitals	-0.0325	0.531*	1.058
% of families in PSF	1.327	-1.846	-6.158
Average visits of PSF agents	0.000319	-0.0178	-0.0371

Variables	(1) Poisson	(2) Negative Binomial	(3) Hurdle
Basic health expenditures in 2010	-0.00438	-0.00198	0.00803
Surveillance expenditures in 2010	1.107***	0.527***	1.672***
Res1: Lagged Dengue Eq. ^{##}	0.00315*	0.0105***	0.0269***
Res2: Spatial Lagged Dengue Eq. ^{###}	-0.00954*	-0.0101***	-0.0180**
Res3: Health Expenses Eq. [#]	-0.894***	-0.355***	-1.131***
Akaike information criterion (AIC)	193.47	8.40	10.36
Squared correlation (predicted & observed)	0.65	0.21	0.35
Total observations	5544	5544	3,915

Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

[#] Residuals from the reduced form for expenditures for epidemiological surveillance per person in 2010. List of instruments: All exogenous + lagged real expenditures p.p. (2005 to 2009)⁴⁴. F-test for the excluded exogenous variables: 89.16***.

^{##} Residuals from the reduced form for dynamic component (2009). List of instruments: All exogenous + lagged dengue cases (2003 to 2008). F-test for the excluded exogenous variables: 37.15***.

^{###} Residuals from the reduced form for neighbors dengue notifications in 2010. List of instruments: All exogenous + spatial lagged from exogenous variables. F-test for the excluded exogenous variables: 412.92***.

The Poisson and negative binomial models showed convergent results, but the latter had lower information criterion (AIC) value, while the former seemed to fit the data better, as the squared correlation between predicted and observed values shows. The joint test for the instrumental variables (Table 2.5 notes) shows they are relevant to explain the endogenous variables and the statistical significance of the residual variables indicates these variables might have captured the endogeneity of the variables.

There is evidence of spatial contagion from neighboring municipalities, as the coefficient for the spatially lagged variable is positive and statistically significant for all the models. Another important result is the non-significant time lag variable effect, even after correcting the potential endogeneity. This evidence suggests that the epidemics did not have significant time dependence and seemed to be more affected by other variables than by previous epidemics in the municipality.

The variable that indicates the level of municipal urbanization indicates a significant and positive relationship with dengue risk (the vegetation index coefficient also indicates a statistically significant effect that corroborates this idea). In line with this result, there are also significant differences in dengue incidence among the Brazilian

⁴⁴ Many combinations of lagged expenditures were tested before the final specification.

biomes, with more dengue cases in the four most important biomes: Amazonia; Cerrado; Caatinga; and Mata Atlântica. The Pampas and Pantanal biomes exhibited less dengue incidence than the others.

When it comes to the income variables, the variables that measured average income are not significant, but there seems to be a positive correlation between income inequality (Gini coefficient) and dengue. There is also some evidence that ownership of radios and TVs might reduce the dengue problem, which suggests that educational programs of the federal government in the media might be effective in reducing dengue incidence.

In reference to sanitation conditions, the average marginal effect does not show a significant effect on dengue cases, with income inequality being more important to detect this social effect, mainly because this study considers municipal averages as variables, without detecting the distributional aspects of sanitation within the municipality.

Regarding the health inputs variable, the PSF frequency of visits showed results in direction of dengue risk reduction in some of the simulations, but this evidence vanished in the final specification. The local municipal expenditures for epidemiological surveillance present a positive and significant effect on dengue, even after correcting the reverse causality bias. This result might indicate the ineffectiveness of such expenditures, mainly due to delay in which the expenditures are incurred (see Section 2.3.3 for more details).

2.4.2 Step II: Average climate results

The average marginal effects for the climate variables are analyzed for ranges of the variable values using the Poisson model. The following figures show the percentage risk effects estimated by value ranges of the variables (effects on the level of dengue variable are presented in Appendix A.2.5 and clearly illustrate the nonlinearities of those variables). The three climate variables considered (in nonlinear form) are rainfall, air temperature and relative humidity during summer, as this season is the most relevant when it comes to dengue in Brazil.

Figure 2.3: Average marginal effects of temperature, in °C, on % dengue risk (summer average temperature from 1980 to 2009)

Source: Prepared by the author. IC Min and IC Max: lower and upper bound of the 95% confidence interval, respectively.

Figure 2.4: Average marginal effects of relative humidity, in percentage, on % dengue risk (summer average temperature from 1980 to 2009)

Source: Prepared by the author. IC Min and IC Max: lower and upper bound of the 95% confidence interval, respectively.

Figure 2.5: Average marginal effects for average rainfall, in mm, on % dengue risk (summer average temperature from 1980 to 2009)

Source: Prepared by the author. IC Min: lower bound of the 95% confidence interval; IC Max: upper bound of the 95% confidence interval.

The most relevant climate variables that explain dengue incidence are temperature and relative humidity. The estimated effects of the former suggest that in municipalities where the average summer temperature is lower (from 21 to 25 °C) than the Brazilian average, long-term increases in temperature might cause an additional risk of the disease. In municipalities where the average temperatures during summer are higher than 25 to 25.5 °C, increases in average temperature might reduce the risk of dengue, as mosquitoes might find it difficult to survive due to the higher temperatures.

When it comes to the relative humidity, the results indicate that as relative humidity increases, the risk of dengue rises. The non-significance of the rainfall estimations suggests that a humid environment (caused by the rainfall conditions) seems to be more important than average long-term rainfall conditions. Moreover, part of the rainfall effect might have been captured by the former variable. It can be logical to expect that short-term rainfall conditions may be more important to explain the water accumulation effect than long-term rainfall patterns.

The long-term estimated temperature coefficients can be used to project the increased (or decreased) risk of dengue due to expected climate changes. The climate information used to calculate this risk was CPTEC/INPE forecasts for the micro-regions

(summarized in Table 1.2 in Chapter 1) for two future time periods: 2040-2069 and 2070-2099.⁴⁵

The increase or decrease in incidence of dengue due to climate changes is exhibited in Figure 2.6. The effect is calculated by multiplying the marginal effects by the expected change in temperature, forecast by INPE. Note that for each municipality, the marginal effect is different, since the average temperature differs among the regions. The results are partial effects and assume that all other variables are maintained at the same level.

⁴⁵ See Chapter 1 for more details.

Figure 2.6: Potential changes in dengue risk due to expected temperature changes, 2040-2069 (left) and 2070-2099 (right), Brazilian municipalities, Scenario B2

Notes: High reduction: lower than -80%; Medium reduction: from -80% to -40%; Low reduction: -40% to -2%; No change: -2% to 2%; Low increase: 2% to 40%; Medium increase: 40% to 80%; High increase: higher than 80%.
Source: Prepared by the author.

If the climate changes expected occur, the most affected areas will be the southern and southeastern areas in Brazil, as these areas might acquire better climate conditions for the mosquitoes' development. Minas Gerais, São Paulo, Mato Grosso do Sul, Rio de Janeiro, Bahia, and Goiás are the states with the highest rates of dengue and might have additional risk of dengue cases if climate changes occur. When it comes to the areas where the risk will decrease, Mato Grosso, Tocantins, Rodônia, Amapá, and Roraima are the states where dengue had high incidence in 2010 and climate changes might reduce the probability of mosquito development. The 2040-2069 forecasts only indicate a smooth transition toward 2070-2099 predictions.

Those findings are in agreement with some projections of the change in spatial distribution of infectious diseases in countries. IPCC (2007) emphasized that some studies found positive evidences of changes in range and transmission potential of malaria in the warmest areas in Africa.⁴⁶

⁴⁶ The same report highlights that the factors that directly shape the health of populations such as education, health care, public health initiatives, infrastructure and economic development are also fundamental for disease propagation.

2.4.3 Step III: Short-term climate results

Other relevant information from the estimated effects is related to the short-term effects of climate on dengue risk. The most important short-term impact is rainfall deviation from long-term average. The estimates indicate that once observed rainfall is close to normal conditions, the risk of dengue is reduced when compared to greater deviations. In other words, *ceteris paribus*, the estimates show that the risk of dengue increases when the observed rainfall deviates from average. This is an intuitive effect when it comes to rainfall above normal conditions, which affects the level of reservoirs and, consequently, might increase the mosquitos' reproduction chance. When it comes to the relative humidity effect, smaller decreases in humidity in the short-term might slightly increase dengue risk in the short term.

Figure 2.7: Average marginal effects for 2010 temperature deviation (summer, in degrees Celsius deviation from long-term average per month)

Source: Prepared by the author. IC Min/Max: lower/upper bound of the 95% confidence interval, respectively.

Figure 2.8: Average marginal effects for 2010 relative humidity deviation (summer, in percentage deviation from long-term average per month)

Source: Prepared by the author. IC Min/Max: lower/upper bound of the 95% confidence interval, respectively.

Figure 2.9: Average marginal effects for 2010 rainfall deviation (summer, in mm deviation from long-term average per month)

Source: Prepared by the author. IC Min/Max: lower/upper bound of the 95% confidence interval, respectively.

The coefficients estimated for the short-term climate effects can be used to help anticipate the risk of dengue due to specific short-term climate conditions. Socioeconomic conditions are fixed in the short-term and one of the most important determinants for dengue that can change in the short-term is the climate variability

measure for rainfall. For the short-term analysis, INPE/INMET estimates the seasonal predictions for rainfall.⁴⁷

The next figures compare the INPE/INMET predictions with the observed rainfall considering the same criteria: Figure 2.10 shows the climate probability forecast issued in November 2010 by INPE/INMET regarding the following 2011 summer precipitation conditions. The numbers represent the probability of rainfall below normal conditions, inside normal conditions and above normal rainfall in the region; and Figure 2.11 shows the observed precipitation of 2011 summer, classified by below and above normal rainfall conditions (normal conditions are the interval between the first and second tertiles).⁴⁸

⁴⁷ Consensus Climate Forecast: The forecast for seasonal climate is usually expressed by probabilities over the next three months in a given region (below the normal range, in the normal range, or above normal range). These ranges are based on tertiles of the historical distribution.

⁴⁸ For each municipality the 30-year rainfall average is considered as the normal rainfall conditions and then threshold is calculated for above and below normality. Since INPE and INMET forecasts consider as threshold the tertiles of the rainfall distribution, the same procedure is used.

Figure 2.10: Probabilistic forecast consensus of the total rainfall, Dec/2010 to Feb/2011, by probabilities of normal conditions.

Source: CPTEC/INPE/INMET (2012).

Figure 2.11: Observed rainfall compared to the distribution tertiles, Dec/2010 to Feb/2011.

Source: Data from INMET. Prepared by the author.

The INPE/INMET predictions for 2011 summer are best adjusted to the following regions: the northern region of the country, where rainfall above normal had a probability of 45%, and observed rainfall is above the second tertile; the state of Rio Grande do Sul, where the highest probabilities of below-normal and normal rainfall are expected; and the states of Bahia, Minas Gerais, Espírito Santo, Goiás, and north of São Paulo and Paraná, where normal rainfall is expected. Mato Grosso do Sul is the only state that presented more below-normal rainfall values than expected by INPE/INMET.

The next figure shows the evolution of dengue cases in 2011 compared to 2010. The numbers reflect the percentage change in dengue incidence from 2010 to 2011. Fewer dengue cases were observed in the central part of Brazil (Goiás, Mato Grosso, Mato Grosso do Sul and west of São Paulo and Minas Gerais).

Dengue incidence increased from 2010 to 2011 mostly in the northern and northeastern regions as well as the coastal areas of Rio de Janeiro and Espírito Santo. Most of these regions had above normal rainfall in 2011, which might be one of the explanations for the increase in dengue. The above normal rainfall in the south did not influence dengue much, mainly because this region does not have a historical problem with dengue. Moreover, the long-term evolution of climate seems to be more important than better short-term climate conditions for mosquitoes in this region.

Figure 2.12: Spatial distribution of dengue case variation from 2010 to 2011, Brazilian municipalities.

The short-term rainfall deviations from average might be an important determinant for mosquitoes' short-term development. Once this effect is detected, it is possible to use INPE/INMET rainfall predictions to anticipate the potential risk of dengue due to climate conditions. The other variables being equal, climate is one of the main short-term shifter of dengue incidence.

However, as for all climate predictions, the observed climate might differ from the predicted climate, so those results should be carefully discussed. From the above exercise, it is possible to say there might be an important relationship between these predictions and increase/decrease in dengue. The northern region of the country, where INPE predicted above average rainfall in the summer of 2011, is one of the main areas affected by dengue increase. The predictions are not precise for the Northeast region, but also demonstrated normality of rainfall for the Midwest and western part of the Southeast region, where dengue decreased in 2011.

Climate information can be used to improve decision making regarding policies to prevent dengue in the country. The use of the open-source information can be very cost-effective in detecting population in risk areas and planning integrated actions to reduce this important health problem in the country. The current Brazilian monitoring system is used in a more corrective than preventive way, not using a forecasting mechanism that can anticipate the risk of epidemics.

Other relevant information that can be derived from the model is the social vulnerability for dengue. Disregarding the short-term climate influence and short-term expenditures for epidemiological surveillance, the model generates the incidence rate of dengue due to the other variables: educational, demographic and income variables; regional and social infrastructure information; and average environmental conditions.

Figure 2.13: Dengue incidence ratio predicted by the Poisson model, 2010, Brazilian municipalities.

The above information can be interpreted as current socio-environmental vulnerability for dengue. This rate is based on social and regional vulnerabilities and provides insights into the processes that can positively influence the incidence of dengue in the country. Even cities with good social indicators might also be vulnerable due to average climate conditions or urbanization level, as urbanization leads to more rapid dengue transmission (Rio de Janeiro, west of Paraná, north of São Paulo, and Minas Gerais are good examples of this situation). Another important result is the high dengue vulnerability of the Brazilian border areas and of the Cerrado region.

2.5 Conclusion

This study investigates the relationship between climate variables and the risk of dengue in Brazil, controlling for other important determinants of the disease in the country. Epidemics of infectious diseases such as dengue have important effects on public

spending, besides reducing working time and worker productivity, generating relevant losses in markets.

By using a reduced-form risk equation from a health production approach, the relevance of climate conditions on the dengue epidemics of 2010 could be tested and the importance of some public actions to reduce the risk of dengue could be assessed. This is one of the contributions of this study, as it is the first economic analysis for such an important health problem in Brazil.

The tests performed show that both climate patterns of the region and climate variation are relevant to explain the disease's occurrence in the country, validating the significant role of climate in the incidence of dengue.

The results suggest that climate changes can modify the geographical distribution of dengue in Brazil in the long run. The most affected areas by climate change, if it occurs as expected, will be the southern and southeastern areas in Brazil, as these areas might acquire better climate conditions for the mosquito development. Minas Gerais, São Paulo, Mato Grosso do Sul, Rio de Janeiro, Bahia, and Goiás are the states with the highest rates of dengue and might have additional risk of dengue cases if climate changes are confirmed.

The positive effects associated with climate change is related to the reduction of the dengue problem in the northern and some parts of the northeastern regions of the country, as the expected increase in average temperatures might reduce the comfortable climate conditions for mosquitoes.

The significance of urban variables corroborated that dengue in the country has urban characteristics. An important effect detected is the reduction in dengue cases in municipalities where households have more TVs and radios, indicating a positive effect of integrated media campaigns, typically promoted by the federal government, in reducing dengue. This is normally done through a combination of public education about elimination of breeding sites to kill mosquito larvae.

The expenditures for epidemiological surveillance show a positive and statistically significant effect on dengue, even after correcting for the reverse causality bias. This is an important result that can be an indication of the ineffectiveness of such expenditures in the current form: two to three months after observing an epidemic (according to SINAN, 40-50% of dengue cases in Brazil occur in the first three months of the year).

Those expenditures are also made locally, not controlling for the infected mosquitoes that cross municipal borders. Moreover, this neighborhood transmission effect (spatial effect) is also statistically significant; suggesting that dengue control actions should be integrated with neighboring municipalities.

The estimation of the effects of the determinants of dengue helps to understand the epidemic transmission in the country, facilitating public administrators' further investigation in identifying high-risk areas. One dengue notification in a neighboring municipality increases the risk of dengue from 1 to 3% in the municipality.

Another important result is the non-significance of dynamics in dengue incidence, since the statistical significance of the time lag variable effect is nil after controlling for its potential endogeneity. This evidence suggests that epidemics do not have significant time dependence and seem to be more affected by other variables than by previous epidemics.

When it comes to the relevant short-term climate effects, they are basically related to rainfall and humidity conditions and the main results indicate both lack of rain and excess of rain increase dengue risk when compared to normal rainfall. This effect might be counter-intuitive at first, but must be interpreted together with the long-term climate effects. As dengue cases are more expected in humid environments – average long-term humidity effect-, drier places need more rainfall on average to be affected by dengue and humid places need less rainfall for mosquitoes to develop.

Based on this short-term effect, it is possible to use INPE/INMET rainfall predictions for the next season to anticipate the potential risk of dengue due to the climate conditions, since climate is one important short-term shifter of dengue incidence. The exercise in Section 2.4.3 suggests there is an important relationship between those predictions and increase/decrease in dengue. Again, the use of the open-source information can be very cost-effective in detecting risk areas and planning actions to reduce this important health problem in the country. The current Brazilian monitoring system does not use a forecasting mechanism that can anticipate epidemics.

Finally, the incidence rate for social and regional vulnerabilities was estimated, as a proxy for current vulnerability for dengue, and provided some relevant insights into the average processes that can positively influence the incidence of dengue in the country.

3. CLIMATE CHANGE AND ADAPTATION IMPACTS ON BRAZILIAN AGRICULTURE

3.1 Introduction

According to the United Nations, the world population might reach approximately 10.6 billion people by 2050 (UN, 2004). Among several potential problems that will arise from this expected population growth is greater demand for food. According to the most pessimistic assumption for population growth until 2050, farmers would have to increase food production from 70 to 100% to meet this possible global demand from population increase.⁴⁹ Consequently, the agricultural sector will be challenged to ensure future food security.

This situation requires an understanding of the potential impacts that changes in climate might have on agricultural production, since climate is an important factor influencing agricultural markets. Expected climate change, for example, can bring gains or losses to these markets, making it an important issue to consider for long-term sustainable planning.

This chapter begins the discussion on the effects of climate on crops and livestock⁵⁰ and the next chapter continues the analysis with a different point of view. Those impacts can be subdivided into: the average climate conditions that can influence farmers' decisions on what crops/animals to grow/raise; and the extreme weather events can cause harmful effects on agricultural output. The latter effect is analyzed at Chapter 4, while the former is the subject of this chapter.

The estimation and testing of hypotheses concerning the magnitude and direction of these effects can help planning measures to adapt to the forecast future climate conditions. Within this context, the two main questions addressed in this chapter are:

- I) *How will climate changes, if confirmed, affect farmers' profits and production in Brazil?*
- II) *How can farmers adapt to deal with such possible changes?*⁵¹

⁴⁹ Estimated based on FAO (2011a) and USDA (2010). Both sources consulted in May, 2012.

⁵⁰ Beef and cow's milk production, which represent approximately 55% of livestock production value.

⁵¹ According to FAO (2011b), the improvement of agricultural systems' flexibility and of agricultural productivity is essential for climate adaptation, as occurred in the past, when the management of irrigation

An important caveat must be made: this study only analyzes the forecast climate change effects on agricultural profits; although it is known that agriculture is an important greenhouse gas (GHG)⁵² emitter (DALE, 1997). Therefore, the analysis is restricted to issues of adaptation rather than mitigation of climate change.⁵³

In order to discuss and analyze the problem raised, this study uses a profit function approach testing if the average climate exogenously influences farmers' choice to maximize profits. It is also tested if farmers might deviate from their optimal choices (an analysis that is detailed at Chapter 4), leading to a profit frontier approach. The following steps are carried out in this analysis:

- i) Testing the average climate relevance on farmers' outcomes;
- ii) if average climate is statistically relevant, average climate marginal effects on production are estimated per product;
- iii) by using CPTEC/INPE forecasts for climate changes in Brazil, the possible losses/gains in production are estimated by region;
- iv) from the estimated losses from climate changes, the compensation measures are calculated using the impact of technological variables on production. These measures can be interpreted as potential adaptation to climate changes.

This analysis is applied to Brazilian farming and livestock breeding. Brazil is one of the main grain producers and exporters in the world. In 2009-2010 the country was responsible for 5.8% of total grain exports, and in 2010-2011, this rate was about 4.01% (INTERNATIONAL GRAINS COUNCIL, 2009). Besides that, Brazil is of continental proportions, with enormous climate variability from the equatorial North, which is 4,000 Km from the temperate South.⁵⁴

technologies changed agriculture and ensured food security after the Second World War (ADAMS, 1989).

⁵² According to IPCC (2007): "GHG are the gaseous constituents of the atmosphere, both natural and anthropogenic, that absorb and emit radiation at specific wavelengths within the spectrum of thermal infrared radiation emitted by the Earth's surface, the atmosphere itself, and by clouds. This property causes the greenhouse effect."

⁵³ According to the last Brazilian GHG Inventory, whose results are expected to be presented officially at the end of 2012, agriculture represented 19% of the GHG emissions in Brazil from 1990 to 2005. This might cause endogeneity in average climate variables. However, the effect of anthropogenic factors on climate is still not certain and the effect is not direct, as other countries' emissions, such as from China and the USA, might have a greater influence on Brazil's climate than Brazilian emissions. For this reason, agriculture is an important emitter, but this fact is not relevant for Brazilian climate (BRAZIL, 2012).

⁵⁴ However, the method presented in this study can be applied to any country where the necessary information is available.

The main objective of this chapter is to identify the expected climate change effects on Brazilian agriculture in terms of profits and production. For this purpose, an important hypothesis to test is that farmers only observe the average climate of their region when deciding on the type and amount of crops to grow (or animals to raise). Thus, climate can be considered an important input for farmers' decisions when maximizing their profits.

3.2 Literature review

Studies measuring the impacts of climate on agricultural outcomes are normally based on two different modeling approaches: the Ricardian or hedonic approach (MENDELSON, 1994; SANGHI *et al.*, 1997; EVENSON; ALVES, 1998; DESCHÊNES; GREENSTONE, 2007; FÉRES *et al.*, 2008) and the agro-economic or crop approach (LANG, 1999; FÉRES *et al.*, 2010; NADAL, 2010). While the former measures the influence of climate on land values, the latter uses farmers' production structure to measure the optimal allocation of different crops to inputs and fixed factors.

Specifically, the agro-economic approach can be used to assess the possible impacts of climate change on agricultural productivity and the reduced economic losses of farmers from implementation of particular adaptation practices. This model is more flexible when accounting for output and input variation in the model (FÉRES *et al.*, 2008), but it does not take into account products not initially considered in the approach. The Ricardian approach is centered on the idea that long-term productivity is reflected in land values and implicitly incorporates producers' change of behavior from new climate regimes into the analysis.

The choice between these two approaches is based on the relative advantages and disadvantages and on their data requirements. Some authors argue that studies following the Ricardian approach produce more aggregated results, which might be an obstacle for the measurement and proposal of adaptation measures (FÉRES *et al.*, 2010; NADAL, 2010). This study adopts an agro-economic approach to try to identify the specific effects of climate on agricultural yields as well as to test the possible adaptation measures to deal with the expected harmful effects of changes in climate on crops and livestock. The agro-economic literature bases the analysis on agricultural profits and production functions, which are briefly discussed next.

The first subsection indicates the reasons for considering an efficiency analysis in an agro-economic model within the context of agriculture, followed by the discussion of using the profit approach instead of a production function.

3.2.1 Profit efficiency in agriculture

Once the agro-economic approach is adopted, the next step is to understand how climate can be considered in this approach, as it impacts the model choice. Demir and Mahmud (2005) argued that the local agro-climatic conditions are historically known by farmers and therefore should not be treated as random, since they influence producers' choices. As a result, changes in average climatic conditions can modify the behavior of farmers as they take into account local climate patterns (temperature and precipitation) in deciding on the output-input mix (KUMBHAKAR; LOVELL, 2000; KUMAR, 2009). Thus, assuming that farmers only observe the past climate conditions (average climate), it is reasonable to consider that they take average climate into account when choosing the type of crops/animals that will be grown/raised, so climate can be considered a key input for crop and livestock outputs.⁵⁵

Nevertheless, another relevant climate effect on agriculture is related to extreme weather events during growing and harvesting seasons, which are not observed by farmers when choosing the output-input mix that optimize their outcomes. Those extreme events can cause important damages which divert farmers from their optimal allocation. The errors/deviations in the production decision are assumed to translate into lower profits for producers, causing inefficiencies (ALI *et al.*, 1994).⁵⁶ This short-term climate concern leads to the adoption of an efficiency analysis, which measures and helps to identify variations of the physical and financial performance achieved by

⁵⁵ This study assumes that farmers do not have information about the next season's climate (or accurate information about it). The arguments in favor of this hypothesis are: (i) access to short-term forecasts is higher among large and medium farmers, who represent a small proportion of total farmers; (ii) the longer the weather forecast horizon, the less accurate it will be. For perennial crops, livestock and forest products closer forecasts might not be useful, although they are more reasonable for annual crops.

⁵⁶ This idea can be explained by an example: assume two identical farmers (farmer 1 and farmer 2) that produce the same crop, using the same amount of inputs, and having similar average climate conditions. If farmer 1 is affected by a drought while farmer 2 is not, the former will probably have lower production/profits compared to the latter farmer (lower profits might arise both from harvest failure and from the need to use more inputs to reduce damages). This difference in outcome between the farmers is called inefficiency. This example helps to motivate the use of an inefficiency approach, or efficient analysis, to consistently measure farmers' decisions.

farmers operating with the same environmental and economic constraints (WILSON *et al.*, 2001).⁵⁷

Ali and Flinn (1989) argue that in order to measure efficiency, a production function approach may not be appropriate when the population of farmers faces different prices and has different factor endowments.⁵⁸ When facing heterogeneous farms, the authors urge the use of stochastic profit function models.

The stochastic profit function model, or profit frontier approach, besides providing a compact form to summarize a multiproduct technology⁵⁹, is an effective way to introduce the theoretical constraints into the analysis (MUNDLAK, 2001). Moreover, this approach allows ascertaining a profit efficiency measure, which captures farmers' failure to meet the production plans defined. The next section details the theoretical and empirical developments which support the measurement of the intended effects.

3.3 Profit frontier approach

This section presents the profit frontier model, briefly motivated by the above literature review, and discusses which agricultural prices farmers consider when deciding to produce specific products.

3.3.1 Profit frontier

The profit approach is a partial equilibrium model based on microeconomics production theory. By specifying a profit function, which is an objective function, it is possible to obtain farmers' optimal input-output allocation by optimizing profits, choosing the allocation. It is assumed that producers allocate their g variable inputs to s types of production. The number of outputs plus the number of inputs represents the m products considered in the analysis (namely, *netputs*), such that $m = s + g$.

Producers decide on the amount of production and the amount of inputs to be purchased

⁵⁷ The method discussed at this section serves as base for the modeling approach used in this chapter and in Chapter 4.

⁵⁸ The production function approach might be biased and inconsistent if the profit maximization is valid, since the input mix is dependent on the error term of the production function (COELLI, 1995).

⁵⁹ According to Kumbhakar and Lovell (2000), profit analysis offers a more complete approach as it better characterizes the production structure and technologies. Hence, this approach generates what is called "profit efficiency", which is defined as the ability of a farm to achieve the highest possible profit (on the profit frontier) given the output and input (*netputs*) prices and levels of fixed inputs of that farm (ALI, FLINN, 1989).

by solving a variable profit maximization problem in a competitive market. Thus, prices are considered as taken, or exogenous.

Besides the prices of inputs and outputs, $p = (p_1, \dots, p_m)'$, each producer faces quasi-fixed inputs (exogenous variables for the time window considered), represented by $Z = (Z_1, \dots, Z_j)'$, which significantly affect the production and factor decision, $q = (q_1, \dots, q_m)'$. The Z vector also includes other exogenous variables, such as local climate patterns (temperature and rainfall) and technological use by the farm.

The vector q denotes the netput amounts: $q_j \geq 0$, when j is an output; and $q_k \leq 0$ when k is an input. Hence, farmers' optimization problem can be described by the following expression:

$$\text{Max}_{\{q_1, \dots, q_m\}} \sum_{j=1}^m \Pi_j(p, q, Z), \text{ subject to a technology } F(q) \leq 0 \quad (3.1)$$

In which $F(\cdot)$ represents a production function that transforms inputs into outputs. Producers maximize a short-run profit function (or restricted profit function) by choosing allocation of multiple outputs and inputs given an endowment of fixed factors (fixed in the short-run): Z and p^{60} . The solution of equation 3.1 gives the optimal allocation, q^* , or the output supply and demand for inputs, which depend on prices and on the fixed factors under the regularity conditions⁶¹:

$$q_j^*(p, Z), j=1, \dots, m \quad (3.2)$$

By replacing the above optimal solution in the profit equation, the optimal profit function is:

$$\Pi^*(p, Z) = \text{ArgMax}_{\{q\}} \sum_{j=1}^m \Pi_j(p, q, Z) \quad (3.3)$$

The profit function is a value function depending on the exogenous variables prices and other quasi-fixed inputs. As already mentioned, prices are exogenous since the approach considers that farmers are price-takers. Agricultural markets are also considered to be perfect – meaning there are no losses due to technical changes. Therefore, farmers are assumed to be fully efficient in optimizing profit (EATON; PANAGARIYA, 1982).

⁶⁰ The transformation function is called the joint production function $g(q/Z)$.

⁶¹ The results depend on the regularity conditions of the profit function, which guarantee the existence of an optimum level (homogeneity, and convexity). See Appendix A.3.2 for more details.

Kumbhakar and Lovell (2000) discussed the same approach, but relaxed the assumption of full efficiency, based on the idea that inefficient farmers can survive in the short run. This idea is further developed in Chapter 4. Considering these potential inefficiencies (τ) in the profit function and assuming the widely used transcendental logarithm (translog) function for farmers' restricted profit function, as first proposed by Christensen *et al.* (1975)⁶², the profit frontier function can be formally described as:

$$\begin{aligned} \ln\left(\frac{\Pi}{p_1}\right) = & \beta_0 + \sum_{j>1} \beta_j \ln(p_j/p_1) + \frac{1}{2} \sum_{j>1} \sum_{k>1} \beta_{jk} \ln(p_j/p_1) \ln(p_k/p_1) \\ & + \sum_{j>1} \sum_{r=1}^f \gamma_{jr} Z_{jr} \ln(p_j/p_1) + \sum_{r=1}^f \delta_r Z_r \\ & + \frac{1}{2} \sum_{h=1}^f \sum_{r=1}^f \theta_{hr} Z_h Z_r - \tau \end{aligned} \quad (3.4)$$

In which $j, k = 1, \dots, m$; $r, h = 1, \dots, f$; and $\beta, \delta, \theta, \gamma$, and τ are parameter vectors. The normalization in product 1 guarantees the homogeneity assumption of prices. Young's theorem holds with this profit function⁶³, guaranteeing the symmetry assumption under the existence of the twice differentiation of Π^* . Appendix A.3.2 gives more details on these assumptions, which are part of the regularity conditions for maximization.

Equation 3.4 describes the translog profit frontier function. The normalized translog functional form is locally flexible and generates a closed-form solution. It also allows testing of profit convexity on prices, which means that the matrix of $\beta = [\beta_{jj}]$ is positive semidefinite for $j = 1, \dots, m$.

Using duality in production theory and the Hotelling Lemma⁶⁴, the derivation of the profit logarithm generates output and input profit shares (s_j), which can be formally written as:

$$s_j = \frac{p_j q_j}{\pi} = \beta_j + \sum_{k>1} \beta_{jk} \ln(p_k/p_1) + \sum_{r=1}^f \gamma_{jr} Z_{jr}, \quad j=2, \dots, m \quad (3.5)$$

From the profit share equations, the effects of prices and other exogenous variables can be measured by their estimated elasticities. The form of the elasticities can be calculated

⁶² It is assumed there are no allocative inefficiencies.

⁶³ Young's theorem states that the second derivatives of a twice differentiable continuous function are symmetric, which is also called the equality of mixed partials. This result implies a symmetric Hessian matrix.

⁶⁴ This lemma presumes that the profit function is differentiable.

by a linear combination of coefficients and observed variables:⁶⁵

$$\text{Own-price elasticities (netput } j): \varepsilon_{jj} = s_j - 1 + \beta_{jj}/s_j \quad (3.6)$$

$$\text{Cross-price elasticities (netput } k \text{ on } j): \varepsilon_{jk} = s_k - 1 + \beta_{jk}/s_j \quad (3.7)$$

$$\text{Exogenous variables elast.: } \varepsilon_{jr} = z_r(\delta_r + \sum_{j>1} \gamma_{jr} \ln(p_j/p_1) + \frac{1}{2} \sum_{h=1}^f \theta_{hr} Z_h + \frac{\gamma_{jr}}{s_j}) \quad (3.8)$$

The main advantage of using the normalized translog functional form is the possibility to test convexity and to directly assume linear homogeneity and symmetry. Appendix A.3.2 details these hypotheses, as they are sufficient conditions to ensure that producers are maximizing profits (DIEWERT, 1973). Therefore, the profit frontier equation can be estimated imposing the symmetry and homogeneity assumptions. If the conditions are satisfied locally, or are satisfied for a price range, the results are consistent with maximizing profits (HERTEL, 1984).

Another relevant piece of information from the model is that farmers from different climate conditions in the sample might change technical use of quasi-inputs and inputs due to distinct local climate. In this context, this different behavior among farmers allows the analysis of adaptation to expected climate change through the calculation of possible compensatory responses to climate variations.

3.3.2 Note on agricultural prices

As the previous section shows, agricultural prices are relevant for farmers' decisions. Due to the different time windows between the decision to grow the crop, its harvest and sale of the output, farmers must have price expectations (p^e) when deciding on the crops/animals to grow/raise and the amount of expected return. Thus, farmers' optimization problem can be described by the following expression:

$$\text{Max}_{\{q_1, \dots, q_m\}} \sum_{j=1}^m \Pi_j(p^e, q, Z), \text{ subject to a technology } F(q) \leq 0 \quad (3.9)$$

In which $p_t^e = E_{t-1}(p_t)$, for crop and livestock products, and $p_t^e = p_t$ for other agricultural products such as extraction of wood and other forest products.

The above expectation function expresses that farmers use available information at $(t-1)$ to form expectations about the product prices at t . Several studies have addressed the price expectation problem using adaptive and rational expectations modeling

⁶⁵ The derivation of the elasticities function is exhibited in Appendix A.3.1.

(PASTORE, 1968; NERLOVE, 1956; CASTRO, 2008; NERLOVE; FRONARI, 1998). Rausser and Just (1981) state that the use of future prices, for some agricultural commodities, performed better than econometrically based forecasts.⁶⁶ The problem with future prices is that they do not exist for all agricultural products and also do not have any regional variation.

Barbosa (2011), studying the land-use pattern in Brazil, assumed that farmers' price expectations are the average of real prices observed in the five years before the decision, which is an approach more closely related to adaptive expectations over past prices.

This chapter tests Barbosa's estimated prices and also considers a different approach to the weighting process of Barbosa (2011) by modeling each product price using a dynamic model based on panel data, as Appendix A.3.3 details. One-time lagged prices are also tested, but these prices might not be good approximations, mainly for perennial crops such as coffee, whose prices are highly cyclical.

Based on these developments, Appendix A.3.4 provides the statistical conditions for estimation of the profit frontier equation, taking into account all the theoretical discussion. For the next sections and appendices, the superscript (^e) for prices will be omitted to simplify the equations.

3.4 Data sources and description

Based on the theoretical framework proposed, this section presents the sources of data used, the definition of variables of the model and an overview of the proposed problem based on the data collected.

3.4.1 Data sources

The most detailed information available in Brazil aggregates farmers into administrative districts, such as municipalities. This aggregation is performed to preserve the identity of farmers. In addition to that, data based on responses by fewer than three farm establishments are not reported for the same reason. Despite the loss of desired information on individual choice of farmers, this procedure does not preclude the analysis, as there are local homogeneities, mostly related to environmental and logistic

⁶⁶ Performance was measured in mean squared error terms.

conditions, among the grouped farmers (DISCH, 1983). Moreover, the price variability among regions is preserved. Pastore (1968) minimizes the aggregation problem when the model is estimated using the information available on the smallest regional unit.

The main agricultural data source in the country is the Brazilian Agricultural Census, conducted by the IBGE. The last census was undertaken in 2006, for which the reference period encompasses the period from 1 January to 31 December 2006. The census refers to cross-sectional data and is the main database used by this study. Panel data, which could generate more accurate results, were not used for two reasons: the data incompatibility between the collection period of the last two agricultural censuses carried out in Brazil (2006 and 1995-96); and the lack of compatible technological variables in the 1995-96 Census. As technological variables are important exogenous inputs of the model (and for the adaptation analysis), this is the main reason to conduct estimations with the 2006 data.

The 2006 Census contains information on output and input quantities and values, land type and use, and farmer and farm characteristics, among other aspects. The output agricultural products considered are divided into nine components of four groups (share of agricultural production value in parentheses):

- i. Annual crops (52.7%): soybeans; maize; others;
- ii. Perennial crops (20.3%): coffee; and others;
- iii. Livestock (22.4%): milk and beef cattle; and
- iv. Forest (4.6%): wood; and other forest products.

These products were chosen according to their weight in each group, in terms of production value in 2006: soybeans and maize represent 24.3% and 14.9% of the total value generated by annual crops, respectively; and coffee represents 34.9% of the value of perennial crops. Beef and milk production represent approximately 55% of livestock production value. The choice of inputs was made using the same criteria, which selected four inputs: land, and fuel (quasi-fixed inputs); and labor and fertilizers (variable inputs). The total amount of fuel used by the farm can be considered a proxy for capital stock of the farm, according to Burniaux and Truong (2002).

The fuel variable is generated by summing the information on different energy sources. All types of fuels were converted into energy generation, kilocalories (kcal), using the

density and power capacity figures from Petrobras and other sources of information.⁶⁷ Labor prices were calculated as the average rural wage equal to the sum of farm workers' monthly wages divided by the number of employees. Employees include permanent workers, temporary workers, farm owners, and other workers, as well as farmers' relatives.

The technological variables available in the 2006 Census are chosen based on the study of EMBRAPA (*Empresa Brasileira de Pesquisa Agrícola*, the government agricultural research agency) and IBGE on the knowledge, information and technology in agriculture in Brazil (IBGE, 2010). According to their technological variables mapping, the following aspects can be used as indicators for rural technology: use of irrigation; proportion of establishments with mechanical harvesters; municipalities with 50% or more of the harvested area planted with certified and transgenic seeds; municipalities with 50% or more of agricultural establishments having access to technical assistance; number of establishments with tilled area; number of establishments with eucalyptus production; and for livestock, municipalities that have establishments with artificial insemination; animal screening; use of industrial feed; and animal confinement. Most of these data are available in the 2006 Census as a percentage of farmers in the municipality that adopt the technology.

Complementary data regarding Brazilian agriculture is available from the Municipal Agricultural Survey (PAM) conducted by IBGE. This survey also aggregates farmers by municipalities and collects important information regarding yearly crop production, physical and financial production. These data are important to analyze farmers' price expectations about the crop and livestock markets. More information on how these prices were calculated and used is given in Appendix A.3.3.

The historical climate data were obtained from INMET, as Chapter 1 describes. The long-term average is calculated based on the year of the census (2006), so the climate information take into account the 30-year average of past data (from 1976-2005) to compute the current climate pattern observed by each farmer. The average is calculated by season, generating the long-term seasonal mean.

⁶⁷ See the following sources, consulted in November 2011: Petrobrás (2011) and ABEPRO (2011).

The abovementioned data sources allow the measurement of the climate effects on agricultural outcomes. However, to forecast the potential climate change impacts on these markets, information about climate change forecasts in Brazil is needed. Chapter 1 summarizes the information on these forecasts, which in Brazil are produced by CPTEC/INPE. Two scenarios and two different future periods are used in the forecasts: A2 and B2; 2040-2069 and 2070-2100, respectively.

3.4.2 Agricultural and climate overview

In general, the Brazilian crop and livestock production is distributed between two regions: the temperate region, covering the South and Southeast regions; and the tropical Midwest region. There are different farming and livestock patterns within each of these regions.

Data from the last Agricultural Census show that, overall in Brazil, 41.8% of farms are focused on livestock production and 50.4% on growing crops (both perennial and annual crops). In 2006, there were more than 3.6 million farms in the country. The median size of the farms is 13 hectares and this average is higher for the southern, northern and southeastern regions.

Annual crops generated the highest total agricultural revenue in 2006, followed by livestock and perennial crops. Annual crops also accounted for more than 85% of the planted area in the country.

Figure 3.1: Total revenues by product in billions dollars*, Brazil, 2006

* Converted to dollars by the 2006 average exchange rate (Source: SISBACEN PTAX800)

** Fisheries, seedlings, flowers, aquacultures.

Source: Brazilian Agricultural Census of 2006. Prepared by the author.

Since Brazil is a huge country in terms of area, its climate varies considerably. The tropical area (northern part of the country) has higher average temperatures and little variability during the year. Rainfall in Brazil has seasonal patterns, typically being heavier during the summer, from December to March (Figure 3.3).

On the other hand, the southern most areas can have brief frosts/snowfall during the winter (June to September). The North region is more humid and the rainy season lasts longer in this region, contrasting with the climate of the neighboring Northeast region, where there are higher temperatures but less rainfall. The widespread semi-desert *caatinga* vegetation is a reflection of the climate pattern of this region.

Figure 3.2: Average monthly temperature from 1975 to 2005 by season, in degrees Celsius.

Figure 3.3: Average monthly precipitation from 1975 to 2005 by season, in millimeters.

Based on Cunha *et al.* (2012), this study considers only average summer and winter seasonal climate information. The authors state that Latin American countries in general do not have well defined seasons, so that summer and winter are representative seasons when it comes to the region's climate patterns.⁶⁸

3.4.3 Descriptive statistics

The next tables and figures show the main summary statistics and description of the data used in the analysis. The tables are subdivided into groups of variables from similar characteristics to facilitate visualization of the information.

⁶⁸ Cunha *et al.* (2012) based their analysis on Seo and Mendelsohn (2008) and Seo (2010, 2011).

The following figure illustrates the profit variable values. The variable profit by municipality is calculated using the total value of production generated by the municipality less the expenses for variable inputs (labor and fertilizer). The graphs below show the histograms of the variables both in level (in thousands of reais) and in logarithm.⁶⁹

Figure 3.4: Profit values in level (left) and logarithm (right), thousand R\$, 2006 Census

The profit distribution indicates a log-normal distribution for profits, which corroborates the use of logarithm in profits, as the translog functional form states. Negative and zero profits represented four to five percent of the total observations and vanished with the logarithm operator. Table 3.1 summarizes the information about the production of crops, forest products and livestock products (beef and milk). This information is important to give better sense to the production data.

Table 3.1: Information on agricultural production, 2006 Census

Variable	Total obs.	Mean	Std. Dev.	Min	Max
<i>Production information</i>					
Maize (tons ⁷⁰)	5548	6,826.75	25,470.49	0.00	596,645
Soybeans (tons)	5548	7,057.82	37,722.83	0.00	1,360,187
Other annual crops (tons)	5548	75,534.18	343,187.50	0.00	7,330,239
Coffee (tons)	5548	463.31	2,244.40	0.00	67,361
Other perennial crops (tons)	5548	3,855.21	18,816.18	0.00	479,138
Wood (m ³)	5548	7.34	53.93	0.00	1,675
Other forest products (tons)	5548	160.58	2,148.29	0.00	131,572
Milk (thd liters)	5548	3,057.84	5,776.21	0.00	125,104
Beef amount (cattle)	5532	604.93	948.66	0.00	10,565

⁶⁹ The graphs showing the levels of profits are restricted to 400 million reais. Above this value, 7% of the municipalities have profits greater than this value, making it difficult to visualize the distributional patterns. The profit variable is calculated based on the 5-year average price, which was chosen as the best price expectation for farmers.

⁷⁰ Metric tons.

All quantities are given in tons except milk production, which is expressed in thousand liters, and wood production, given in thousand cubic meters. Apart from the aggregated groups of crops, the soybean and maize averages suggest that farms that cultivate those products are larger in terms of production than coffee plantations.

When it comes to the physical amounts of inputs (Table 3.2), quantity of fuel (proxy for capital stock in the model) is measured in thousand kcal of power according to the available information on transformation units. Land quantity is measured in hectares. Fertilizers are measured by total fertilized area in the municipality. Labor amount is measured in number of rural workers in the municipality. The price information is generated by dividing total expenses for labor and fertilizers by the quantities, what generates implicit price measures.

Table 3.2: Information regarding use of inputs, 2006 Census

Variable	Total obs.	Mean	Std. Dev.	Min	Max
<i>Input prices (Thousand reais per employee or hectares)</i>					
Labor price (k R\$/person)	5552	1.09	2.67	0.00	48.25
Price per fertilized hectare (kR\$/ha)	5552	0.24	0.32	0.00	4.89
<i>Input quantities (in thousand Kcal/hectares/employees)</i>					
Total fuel (in k kcal)	5548	4,715	9,715	0.00	233,783
Total available land (ha)	5548	41,602	86,862	0.00	3,719,038
Total employees (number)	5548	4,698	7,761	0.00	306,279
Total fertilized area (ha)	5548	7,240	21,934	0.00	595,488

The next table describes the technological variables available in the Brazilian Agricultural Census. All variables are measured in percentages, as the Census questionnaire only permits farmers to answer if they have this kind of activity or not.

Table 3.3: Information regarding production, 2006 Census

Variable	Total obs.	Mean	Std. Dev.	Min	Max
<i>Technological Information</i>					
Percentage of mechanical harvesting	5548	0.03	0.13	0.00	1.00
Percentage of certified seeds	5548	0.30	0.32	0.00	1.00
Percentage of transgenic seeds	5548	0.04	0.11	0.00	1.00
Percentage of certified or transgenic seeds usage	5548	0.33	0.35	0.00	1.00
Percentage of cattle confined	5548	0.03	0.07	0.00	1.00
Participation of artificial insemination	5427	0.08	0.14	0.00	1.00
Percentage of tilled area	4691	0.07	0.16	0.00	0.89
Percentage of irrigated area	5544	0.02	0.06	0.00	0.64
Percentage of animal tracking	5548	0.05	0.07	0.00	1.00
Percentage of industrial feed usage	5548	0.01	0.03	0.00	0.50

The average percentage of farmers using certified seeds is about 30%. The analysis of the averages shows that, except for the use of certified seeds, almost all factors have limited use. The low percentage of irrigated area also is noteworthy.

3.5 Results

The next subsections present the models estimated to test the climate patterns' importance on rural profits. Once these effects are tested, the final model is estimated and the relevant elasticities calculated. At the end of the section, the forecast climate change effects are calculated and the measures of adaptation are presented.

3.5.1 Stages of model estimation

To test the importance of climate patterns on farmers' profit, the nested models 1 and 2 are estimated:

Model 1: Normalized profit frontier model against output and input prices (3 versions of prices: estimated, one time lag and 5-year lagged average):

$$\ln\left(\frac{\Pi_i}{p_{1,i}^e}\right) = \beta_0 + \sum_{j>1} \beta_j \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) + \frac{1}{2} \sum_{j>1} \sum_{k>1} \beta_{jk} \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) \ln\left(\frac{p_{k,i}^e}{p_{1,i}^e}\right) - \tau_i + v_i \quad (3.10)$$

Model 2: Normalized profit frontier model against output and input prices and long-term climate variables:

$$\begin{aligned}
\ln\left(\frac{\Pi_i}{p_{1,i}^e}\right) = & \beta_0 + \sum_{j>1} \beta_j \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) + \frac{1}{2} \sum_{j>1} \sum_{k>1} \beta_{jk} \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) \ln\left(\frac{p_{k,i}^e}{p_{1,i}^e}\right) \\
& + \sum_{j>1} \sum_{r=1}^f \gamma_{jr} Z_{jr,i}^1 \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) + \sum_{r=1}^f \delta_r Z_{r,i}^1 \\
& + \frac{1}{2} \sum_{h=1}^f \sum_{r=1}^f \theta_{hr} Z_{h,i}^1 Z_{r,i}^1 - \tau_i + v_i
\end{aligned} \tag{3.11}$$

In which Z^1 is a subset of the exogenous matrix of variables Z .

The relevance of including climate variables in the profit model can be tested by the likelihood ratio (LR) test, assuming model 1 as the null model (H_0) and model 2 as alternative:

$$\text{LR Test} = -2 \ln(\text{likelihood under } H_0) + 2 \ln(\text{likelihood under } H_a) \sim \chi_{df^*}^2 \tag{3.12}$$

In which df^* denotes the difference between the degrees of freedom of the two models.

The completed outputs of the models are presented in Appendix A.3.5. The LR statistic is from 863.43 to 949.65 (depending on the price vector used), much higher than the critical value for 1% significance. Thus, the test indicates that climate variables are relevant to explain farmers' profits.

The next step is to test the significance of the technological variables. In order to perform this test, the following alternative model (Model 3) is compared to Model 1.

Model 3: Normalized profit frontier model against output and input prices of technological variables:

$$\begin{aligned}
\ln\left(\frac{\Pi_i}{p_{1,i}^e}\right) = & \beta_0 + \sum_{j>1} \beta_j \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) + \frac{1}{2} \sum_{j>1} \sum_{k>1} \beta_{jk} \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) \ln\left(\frac{p_{k,i}^e}{p_{1,i}^e}\right) + \sum_{j>1} \sum_{r=1}^f \gamma_{jr} Z_{jr,i}^2 \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) + \\
& \sum_{r=1}^f \delta_r Z_{r,i}^2 + \frac{1}{2} \sum_{h=1}^f \sum_{r=1}^f \theta_{hr} Z_{h,i}^2 Z_{r,i}^2 - \tau_i + v_i
\end{aligned} \tag{3.13}$$

In which Z^2 is a subset of the exogenous matrix of variables Z , which includes only technological variables. The LR test also indicated that the variables in Z^2 are jointly significant to explain profits.⁷¹

⁷¹ LR statistics = 3403.60 to 3571.85, for $df^* = 55$.

The fourth and fifth models (final models) include all variables, to understand their impact on profits and, consequently, to formulate the potential compensation measures. The only difference between them is that while Model 4 includes all cross products of the prices and exogenous variables, Model 5 only adds the exogenous variables iterated with prices.

Model 4: Normalized profit frontier model against all the prices and exogenous variables of the model:

$$\ln\left(\frac{\Pi_i}{p_{1,i}^e}\right) = \beta_0 + \sum_{j>1} \beta_j \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) + \frac{1}{2} \sum_{j>1} \sum_{k>1} \beta_{jk} \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) \ln\left(\frac{p_{k,i}^e}{p_{1,i}^e}\right) + \sum_{j>1} \sum_{r=1}^f \gamma_{jr} Z_{jr,i} \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) + \sum_{r=1}^f \delta_r Z_{r,i} + \frac{1}{2} \sum_{h=1}^f \sum_{r=1}^f \theta_{hr} Z_{h,i} Z_{r,i} - \tau_i + v_i \quad (3.14)$$

Model 5: Normalized profit frontier model against all the prices and exogenous variables of the model (the latter interacted with prices):

$$\ln\left(\frac{\Pi_i}{p_{1,i}^e}\right) = \beta_0 + \sum_{j>1} \beta_j \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) + \frac{1}{2} \sum_{j>1} \sum_{k>1} \beta_{jk} \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) \ln\left(\frac{p_{k,i}^e}{p_{1,i}^e}\right) + \sum_{j>1} \sum_{r=1}^f \gamma_{jr} Z_{jr,i} \ln\left(\frac{p_{j,i}^e}{p_{1,i}^e}\right) - \tau_i + v_i \quad (3.15)$$

Appendix A.3.4 shows the complete results for each model above⁷². The homogeneity and symmetry restrictions are automatically imposed by the translog specification. The convexity assumption is tested and the results are presented and discussed below (Table 3.4). The best fit model, in terms of log-likelihood value, is estimated using the five-year average price as the proxy for expected price by farmers.

Table 3.4: Convexity test for models (4) and (5).

	Model (4)	Model (5)
Convexity test[#]		
Chi-square	127.60***	158.73***

[#] Ho: all β_{jj} are zero; Ha: all β_{jj} are statistically significantly above zero. 10 degrees of freedom.

*** p<0.01, ** p<0.05, * p<0.1

⁷² It is noteworthy that all the models estimated showed that technical inefficiencies are significantly different from zero, according to the LR test on the technical inefficiencies estimations.

The results indicated that, in general, the profit function estimated in Models 4 and 5 can be considered convex.⁷³ Model 4 has more parameters to estimate (252 parameters), which reduces the degrees of freedom and generates larger standard errors, and consequently less significance of the estimations. When comparing the information criteria of the models, Model 4 has smaller results, which indicates better adjustment. However, the Schwartz (or Bayesian) information criterion (BIC) is very similar. Due to the similarity of the BIC and the computation and robustness gain in estimating a model with fewer degrees of freedom (parsimonious criterion), Model 5 is used to generate the intended impacts.

Table 3.5: Fitting information of Models (4) and (5), information criteria and log-likelihood.

Model	Number of parameters	AIC	BIC	Log-likelihood
Model (4)	252	11,974.8	13,599.7	-5,735.41
Model (5)	178	12,480.7	13,622.7	-6,062.33

The following subsections present more details on the estimated results and discuss the partial impacts generated by the Model 5. The price elasticities, which are not a subject of this thesis, are presented in Table A.3.4 in Appendix A.3.5.

3.5.2 Analysis of results

When it comes to the average exogenous variables' effects on farmers' profits, the following table shows the results obtained from Model 5, calculated for the sample average. More disaggregated results are calculated subsequently. The table measures the partial effect of each variable on farmers' profits. As the exogenous variables (r) are included in level and the dependent variable (profits) in the natural logarithmic form, the estimated effects are interpreted as semi-elasticities $\left(\frac{\partial \ln(\pi)}{\partial Z_r}\right)$:

⁷³ Individual tests are also performed. The estimated results are not statistically significant from zero or negative for three individual products: soybeans; beef; and maize.

Table 3.6: Average effect of exogenous variables on profits, semi-elasticities at sample average, 2006 Census.

Variables	Average effect
Fuel quantity (in kcal, <i>proxy</i> for capital)	7.59E-05 ***
Land quantity (hectares)	6.07E-06 ***
% of irrigated area	4.4945 ***
% of certified or transgenic seeds	0.4614 ***
% of confined cattle	0.8357 ***
% of tilled area	1.3436 ***
% of mechanically harvested area	-0.0132
Average rainfall in summer (mm/month, LT [#])	-0.0021 ***
Average rainfall in winter (mm/month, LT [#])	-0.0023 ***
Average temperature in summer (°C, LT [#])	-0.0121
Average temperature in winter (°C, LT [#])	-0.0113

[#] LT: long-term average (from 1976 to 2005).

The quasi-fixed inputs, land and capital (fuel) had the expected signs, meaning that, on average, the more of these inputs used, the greater the profits. The variables describing the use of technological information by farmers showed positive and statistically significant effects on profits. All the variables are measured as percentage of farmers in the region using the technology (except for the percentage of irrigated area). Thus, the results indicate that an increase of 1% of transgenic seed use, for example, can increase farmer profits by 0.46%. The variables measuring local technologies can be ranked by their average importance in explaining profits: % irrigated area; % tilled area; % confined cattle; and % certified or transgenic seeds, in order of importance to improve farmers' profits.

The long-term rainfall averages in summer and winter are statistically significant to explain farmers' profits in Model 5; in general, locations with higher average rainfall have lower agricultural profits. However, these effects can be calculated by product, as these variables have different impacts on the different farm products considered in this analysis. The next table shows the effects on each product's (*j*) profit share by variable (*Z*), $\left(\frac{\partial s_j}{\partial Z}\right)$ from equation 3.5.

By disaggregating the profit impacts into profit share effects, the climate variables show important effects: lack of rainfall impacts only soybean profit shares; while places with higher average temperatures have negative effects on maize, coffee and beef.

Soybeans, other annual crops and other forest products generate more profits when cultivated in smaller areas, as the land quantity effect indicates. When it comes to the fuel variable, the most ‘capital-intensive’ products are maize, other annual crops and wood. On the other hand, milk is the only output that is less capital-intensive. More irrigated area means more profits for soybeans, maize and coffee – the main crops analyzed in this study.

Table 3.7: Average partial effect of exogenous variables (r) on profit shares for product (j), 2006 Census.

Effect on profit shares, by output (γ_{jr})	Soybeans	Maize	Other annual crops	Coffee	Other peren. crops	Milk	Wood	Beef	Other forest products
Fuel quantity	-9.4e-6	1.83e-05**	1.02e-5***	5.5e-06	2.5e-6	-3.93e-5***	1.94e-5***	9.5e-6	4.93e-06
Land quantity	-5.2e-6**	1.8e-6**	-2.99e-6***	2.4e-6***	-3.0e-7	6.16e-6***	2.9e-7	1.0e-6	-1.85e-6***
Irrigated area	6.343**	3.948***	-1.458***	3.992***	-1.859*	-0.451	-1.913***	-7.300***	0.708
Certified or transgenic seeds	-0.962**	-0.114	0.402***	0.072	0.126	0.393	0.241*	-0.147	-0.071
Confined cattle	3.705**	-0.460	-0.301	0.358	-0.019	-0.421	-0.388	-2.143*	0.148
Tilled area	-0.957	-0.835**	-0.178	-0.313	-0.086	1.777***	0.203	0.499	0.308
Mechanical harvesting	0.915	-0.177	-0.172	-0.173	0.813**	-1.002	0.095	-0.659	0.048
Rainfall in summer	0.0237***	-4.6e-04	-9.8e-7	-0.00547***	-0.002*	-0.00893***	7.6e-04	-0.0058***	-2.8e-4
Rainfall in winter	0.0118***	0.0011	-0.0018***	-1.3e-4	-1.8e-4	-0.00827***	-0.00221***	0.0017	8.7e-4
Temperature in summer	1.208***	-0.207**	0.067	-0.264*	0.0014	-0.151	0.0806	-0.726***	0.0125
Temperature in winter	-0.464***	0.046	-0.018	6.5e-04	0.0234	0.0495	0.0063	0.352***	0.0113

*** p<0.01, ** p<0.05, * p<0.10.

For further investigation of the average climate impacts on agriculture, the model allows the calculation of the semi-elasticities of supply for each climate variable and each output considered. The effects can be calculated by municipality, when inputting municipal data into the marginal effect equation in order to identify the specific effects within the country. The average effects' calculation by each municipality's characteristics provides information on how these effects are distributed geographically in the country. The effects are calculated by climate variable (Z^1) and by product (j):⁷⁴

$$\begin{aligned}\frac{\partial \ln(\widehat{q_{jl}})}{\partial Z_{rl}^1} &= \left(\sum_{j>1} \hat{\gamma}_{jr} \ln(p_{ji}) / \ln(p_{1i}) + \frac{\hat{\gamma}_{jr}}{s_{ji}} \right), \text{ if } s_{ji} > 0 \\ \frac{\partial \ln(\widehat{q_{jl}})}{\partial Z_{rl}^1} &= \left(\sum_{j>1} \hat{\gamma}_{jr} \ln(p_{ji}) / \ln(p_{1i}) + \frac{\hat{\gamma}_{jr}}{\widehat{s_{jl}}} \right), \text{ if } s_{ji} = 0\end{aligned}\quad (3.16)$$

The table below summarizes the results obtained by estimating the effects by municipality (i) when $s_{ji} > 0$ (positive production of j in municipality i). Results for municipalities that had zero production are presented in Table A.3.5 of Appendix A.3.5. Table 3.8 shows both the percentage of municipalities where the effects are statistically significant at 10% and the average effect for Brazil.⁷⁵

The average semi-elasticity for Brazil is calculated by weighting the municipality's effect by its share of nationwide production. Thus, the effects better represent the marginal impacts of climate conditions on the production percentage of the country. It also shows the percentage of municipalities that accounted for significant effects (compared to all Brazilian municipalities and compared to the municipalities that produce a positive amount of the specific product).

⁷⁴ These effects are the sum of the profit and profit share effects. See Appendix A.3.1 for the derivation of the effect.

⁷⁵ The statistically insignificant results were disregarded.

Table 3.8: Semi-elasticities, average effects of climate variables on production, by product, results by municipality, 2006 Census.

Output (j)	Summer			Winter		
	% Brazilian munic. with stat. sig effects	% munic. with q>0 and stat. sig. effects	Average effect for Brazil*	% Brazilian munic. with stat. sig effects	% munic. with q>0 and stat. sig. effects	Average effect for Brazil*
<u><i>Rainfall</i></u>						
Soybeans	23%	97%	0.009	22%	94%	0.002
Maize	4%	4%	-0.002	3%	4%	-0.002
Other annual crops	11%	12%	-0.003	92%	96%	-0.011
Coffee	30%	97%	-0.035	2%	7%	-0.003
Other peren. crops	79%	95%	-0.048	4%	5%	-0.003
Milk	93%	97%	-0.182	93%	98%	-0.174
Wood	0%	0%	0.0E+00	26%	99%	-0.690
Beef	94%	99%	-0.017	4%	4%	2.9E-04
Other forest prods.	0%	0%	-3.1E-05	0%	0%	0.002
<u><i>Temperature</i></u>						
Soybean	23%	96%	0.440	22%	95%	-0.227
Maize	78%	87%	-0.764	2%	2%	0.010
Other annual crops	26%	27%	-0.013	9%	10%	0.002
Coffee	24%	79%	-0.281	1%	4%	-0.024
Other peren. crops	1%	1%	-0.021	1%	1%	0.003
Dairy	2%	2%	-0.026	1%	1%	0.002
Wood	0%	0%	0.0E+0	0%	0%	0.0E+0
Beef	96%	100%	-1.870	96%	100%	0.900
Other forest prods.	0%	0%	-4.7E-4	0%	0%	2.4E-4

* Average effect for Brazil is calculated based on the weighted average of significant effects (weighted by the production amount of the municipality)

According to the estimated results, soybean production increases when summer temperature is above average. Increases in long-term average temperature in summer (by 1 Celsius degree), might raise soybean production by 44% on average in the municipalities that produce soybeans in Brazil. This effect is calculated based on 23% of the municipalities that presented statistically significant results (these municipalities represent 96% of the soybean positive production regions). Results in the same direction are observed for the average effect of rainfall in summer and winter. One possible explanation for this effect is that soybeans seem to have greater yields in rainier municipalities (both in summer and winter).

Municipalities with higher average rainfall during summer and winter produce less of most of the agricultural products analyzed: maize; other annual crops; coffee; other perennial crops; milk; wood; and beef. The average effects are not very high for many of these products. The products where output is affected the most are milk (both in summer and winter), coffee and other perennial crops (only in summer), and wood (only in winter). The results suggest that either these products are better adapted to drier places or the larger rainfall averages in the summer might have influenced the results.

The estimated impact of temperature seems to be much higher than of precipitation. The partial effects of higher average summer temperature seem to reduce production of maize, other annual crops, coffee, other perennial crops, milk and beef. Higher winter temperatures might adversely affect only coffee and soybeans.

The next step is to estimate, based on the semi-elasticities estimated by municipality and summarized above, the potential production increase/decrease based on climate change scenarios.

3.5.3 Expected climate change impacts

The basic information regarding the climate change forecasts used is illustrated in the table below. The temperature forecasts are always positive for all scenarios and periods, getting higher when the period of the forecast is extended and when the less optimistic scenario is assumed (A2). As for the rainfall predictions, they seem to be less reliable for long-term change, as Chapter 1 indicated, and they may change from rainier regions to drier regions among the scenarios (e.g., Southeast's forecasts for 2070-2099 in summer and winter).

Table 3.9: Average forecasts for temperature change (in degrees Celsius) and rainfall change (in mm) by region, CPTEC/INPE.

Scenarios	North	Northeast	Southeast	South	Midwest
Rainfall: Summer (S) and Winter (W)					
A2 (S) for 2040-2069	-8.18	-2.37	-2.40	5.15	5.73
B2 (S) for 2040-2069	-2.33	-1.21	2.62	4.18	13.37
A2 (S) for 2070-2099	-13.32	-16.89	-7.99	10.73	0.29
B2 (S) for 2070-2099	-8.11	-0.83	7.06	4.19	6.88
A2 (W) for 2040-2069	-6.02	-0.94	-2.35	-1.77	-0.73
B2 (W) for 2040-2069	-3.88	0.06	-3.96	-3.97	-0.83
A2 (W) for 2070-2099	-8.81	-4.55	-3.26	1.19	-0.34

B2 (W) for 2070-2099	-7.84	-0.10	-4.17	-1.86	-1.01
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Scenarios	North	Northeast	Southeast	South	Midwest
Temperature: Summer (S) and Winter (W)					
A2 (S) for 2040-2069	2.08	1.84	1.86	1.92	2.24
B2 (S) for 2040-2069	1.58	1.57	1.44	1.57	1.71
A2 (S) for 2070-2099	3.80	3.44	3.35	3.31	3.91
B2 (S) for 2070-2099	2.52	2.32	2.16	2.14	2.63
A2 (W) for 2040-2069	2.62	1.77	2.11	2.21	2.54
B2 (W) for 2040-2069	2.16	1.58	1.88	2.11	2.18
A2 (W) for 2070-2099	4.88	3.33	3.92	3.65	4.86
B2 (W) for 2070-2099	3.54	2.40	2.77	2.69	3.40

By using the above summarized forecast climate information, the estimates will be the expected marginal effects on Brazilian agricultural production in the future if climate change forecasts are confirmed.

In order to perform these first calculations, an important hypothesis must be assumed: only average climate is changing according to the IPCC scenarios, i.e., all other variables in the model are assumed to hold at the same level of 2006. The estimations represent partial effect results.

The next tables present the expected gain or loss in production due to climate change forecasts for temperature and precipitation. Two scenarios (A2 and B2) and different periods (2040-2069 and 2070-2099) are used and the results are subdivided by Brazilian regions.

As the estimated coefficients already suggested, soybean production is positively affected by the expected temperature changes, except for the Midwest region, where negative impacts are estimated. For the period from 2040-2069, the expected annual increase in soybean production varies from 18.6 to 38.92% (B2 and A2 Scenarios respectively) due to the temperature change. This result is in line with the IPCC (2007) projections, which suggested that in temperate zones of Latin America soybean yields are projected to increase, while the productivity of some other important crops and livestock is projected to decline.

On the other hand, in the longer term (2070-2099), if forecasts for Scenario B2 are confirmed, soybean production might be negatively impacted by temperature changes, which is a strong and harmful effect in the Midwest region.

Forest products (wood and others) show a very small change due to the expected temperature changes. However, all the other products, which represent 80% of all rural value of production, are negatively impacted by the expected changes in temperature. The most affected products are, in descending order of total relative impact: beef production (in cattle slaughtered); maize; coffee; milk; other perennial crops; and other annual crops. The same order of impacts is observed for the period from 2070 to 2099, but as the temperatures are expected to increase even more, the impacts are much higher (more negative for these products, and more positive for soybeans).

When it comes to the effect of expected rainfall change on production, the results are very different for Scenarios B2 and A2, as the forecasts for each scenario are not convergent (see Table 3.9). The only negative expected impacts in both scenarios are other perennial crops from 2040-2069 and other forest products from 2070-2099, which may be negatively affected by both changes. The expected production changes due to rainfall changes are not as substantial as the expected for temperature changes.

Table 3.10: Total gain (G) or loss (L) in production due to forecast temperature changes in 2040-2069, by product, scenario and region.

Region	North	Northeast	Southeast	South	Midwest	Total G(+) or L(-) Brazil	Total G(+) or L(-) in % Brazil
Temperature Impact (Climate Change: 2040-2069)							
Scenario: A2							
SOYBEANS*	1,256,769	1,673,599	1,440,892	49,865,048	-38,989,356	15,246,953	38.9%
MAIZE*	-940,961	-11,046,631	-9,076,304	-24,431,949	-6,188,341	-51,684,185	-136.5%
OTHER ANNUAL*	2,363,430	-795,426	-16,193,262	12,173,949	-6,536,878	-8,988,187	-2.1%
COFFEE*	-73,005	-236,457	-1,016,339	-182,481	-21,272	-1,529,553	-59.5%
OTHER PEREN.*	15,514	2,726	-757,577	-5,594	0	-744,932	-3.5%
MILK**	-14,192	-128,789	-334,068	-5,305	-247,681	-730,035	-4.3%
WOOD***	0	0	0	0	0	0	0.0%
BEEF****	-740,045	-1,000,526	-1,102,676	-1,699,150	-1,292,849	-5,835,246	-174.4%
OTHER FOR.*	0	356	0	0	-889	-533	-0.1%
Scenario: B2							
SOYBEANS*	917,330	1,274,792	900,263	40,447,784	-36,245,962	7,294,207	18.6%
MAIZE*	-749,648	-8,411,497	-6,794,487	-20,443,810	-5,566,127	-41,965,569	-110.8%
OTHER ANNUAL*	1,887,776	-227,603	-12,317,830	10,042,074	-5,960,411	-6,575,995	-1.6%
COFFEE*	-59,661	-177,405	-779,382	-149,176	-18,804	-1,184,428	-46.1%
OTHER PEREN.*	14,389	9,900	-565,356	-4,723	0	-545,791	-2.6%
MILK**	-11,185	-96,312	-252,660	-4,483	-229,794	-594,434	-3.5%
WOOD***	0	0	0	0	0	0	0.0%
BEEF****	-510,418	-619,203	-680,059	-1,367,814	-1,176,568	-4,354,061	-130.1%
OTHER FOR.*	0	225	0	0	-838	-612	-0.1%

* quantities in tonnes

** quantities in thousand liters

*** quantities in thousand cubic meters

**** in livestock

Table 3.11: Total gain (G) or loss (L) in production due to forecast rainfall changes in 2040-2069, by product, scenario and region.

Region	North	Northeast	Southeast	South	Midwest	Total G(+) or L(-) Brazil	Total G(+) or L(-) in % Brazil
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Rainfall Impact (Climate Change: 2040-2069)
Scenario: A2

SOYBEANS*	-84,922	33,705	-45,860	-2,775,292	2,113,968	-758,401	-1.9%
MAIZE*	-3,179	-424	50,786	60,150	122,632	229,965	0.6%
OTHER ANNUAL*	1,870,560	2,411,420	2,744,026	1,196,964	250,623	8,473,592	2.0%
COFFEE*	108,923	-29,727	46,749	47,011	6,300	179,256	7.2%
OTHER PEREN.*	-137,178	-2,084,958	189,286	465,804	101,358	-1,465,690	-6.9%
MILK**	2,468,913	-1,166,315	1,374,800	4,527,188	696,731	7,901,317	47.7%
WOOD***	8,408	23,639	4,485	25,410	3,084	65,026	160.2%
BEEF****	30,894	-38,474	9,571	31,981	59,599	93,571	2.9%
OTHER FOR.*	3	-7,807	0	36	122	-7,646	-0.9%

Scenario: B2

SOYBEANS*	22,256	-187,906	151,259	191,179	3,360,095	3,536,882	9.0%
MAIZE*	-5,360	-26,761	2,171	15,995	206,737	192,781	0.5%
OTHER ANNUAL*	1,531,291	4,227,624	-840,656	1,000,851	609,711	6,528,821	1.6%
COFFEE*	49,071	-70,459	-137,518	-42,981	4,460	-197,427	-7.7%
OTHER PEREN.*	-967,540	-2,919,632	-523,411	-335,138	124,388	-4,621,333	-21.6%
MILK**	1,586,268	-2,437,395	-709,431	-225,894	985,495	-800,957	-4.7%
WOOD***	6,285	43,942	5,320	20,643	1,834	78,023	191.6%
BEEF****	2,040	-60,127	-40,813	-10,416	85,010	-24,306	-0.7%
OTHER FOR.*	3	-14,565	0	-2	168	-14,395	-1.6%

* quantities in tonnes

** quantities in thousand liters

*** quantities in thousand cubic meters

**** in livestock

Table 3.12: Total gain (G) or loss (L) in production due to forecast temperature changes in 2070-2099, by product, scenario and region.

Region	North	Northeast	Southeast	South	Midwest	Total G(+) or L(-) Brazil	Total G(+) or L(-) in % Brazil
Temperature Impact (Climate Change: 2070-2099)							
Scenario: A2							
SOYBEANS*	1,942,537	3,521,522	2,306,560	85,260,425	-81,817,103	11,213,940	28.6%
MAIZE*	-1,518,937	-23,470,612	-16,514,646	-45,783,020	-13,351,273	-100,638,489	-265.7%
OTHER ANNUAL*	4,019,273	889,865	-32,589,438	21,286,188	-14,349,074	-20,743,186	-5.0%
COFFEE*	-148,524	-428,132	-1,768,682	-339,175	-44,080	-2,728,593	-106.2%
OTHER PEREN.*	18,138	-14,133	-1,364,693	-5,058	0	-1,365,746	-6.4%
MILK**	-23,566	-242,391	-622,280	-8,034	-579,554	-1,475,825	-8.7%
WOOD***	0	0	0	0	0	0	0.0%
BEEF****	-1,263,041	-2,130,711	-1,768,350	-2,768,067	-2,081,425	-10,011,595	-299.2%
OTHER FOR.*	0	614	0	0	-1,129	-514	-0.1%
Scenario: B2							
SOYBEANS*	1,102,501	1,768,379	1,149,193	48,265,176	-58,310,736	-6,025,487	-15.4%
MAIZE*	-985,299	-15,839,250	-10,432,634	-29,399,320	-8,919,977	-65,576,480	-173.1%
OTHER ANNUAL*	2,656,830	-260,572	-20,859,436	13,206,793	-9,641,522	-14,897,908	-3.6%
COFFEE*	-102,498	-291,354	-1,164,000	-215,935	-29,379	-1,803,166	-70.2%
OTHER PEREN.*	13,268	-9,373	-872,686	-1,887	0	-870,677	-4.1%
MILK**	-14,071	-168,827	-398,031	-4,751	-387,315	-972,996	-5.7%
WOOD***	0	0	0	0	0	0	0.0%
BEEF****	-705,947	-1,312,239	-1,002,354	-1,520,074	-1,303,531	-5,844,145	-174.6%
OTHER FOR.*	0	299	0	0	-684	-385	0.0%

* quantities in tonnes

** quantities in thousand liters

*** quantities in thousand cubic meters

**** in livestock

Table 3.13: Total gain (G) or loss (L) in production due to forecast rainfall changes in 2070-2099, by product, scenario and region.

Region	North	Northeast	Southeast	South	Midwest	Total G(+) or L(-) Brazil	Total G(+) or L(-) in % Brazil
Rainfall Impact (Climate Change: 2070-2099)							
Scenario: A2							
SOYBEANS*	-223,029	-469,928	64,122	9,530,944	17,601,262	26,503,370	67.6%
MAIZE*	21	49,702	92,723	-95,208	1,291,440	1,338,679	3.5%
OTHER ANNUAL*	3,345,912	10,438,788	8,958,667	-448,168	-467,594	21,827,604	5.2%
COFFEE*	201,534	114,664	478,961	-183,141	3,716	615,733	24.6%
OTHER PEREN.*	2,254,422	8,096,569	1,272,319	-2,754,413	-46,020	8,822,877	41.3%
MILK**	3,214,071	17,754,066	6,526,194	-15,389,755	-387,895	11,716,682	70.7%
WOOD***	77,164	44,533	7,483	-11,468	1,740	119,452	294.2%
BEEF****	121,846	153,869	66,519	-152,826	-19,358	170,050	5.2%
OTHER FOR.*	0	-13,112	0	-36	-101	-13,249	-1.5%
Scenario: B2							
SOYBEANS*	-106,555	198,036	669,029	3,525,468	16,493,226	20,779,204	53.0%
MAIZE*	-5,278	-23,915	-77,274	-18,195	1,171,188	1,046,526	2.8%
OTHER ANNUAL*	2,832,108	2,726,232	-444,669	1,267,520	-1,393,749	4,987,442	1.2%
COFFEE*	234,901	-79,969	-351,794	-118,511	-13,964	-329,337	-12.8%
OTHER PEREN.*	873,551	869,685	-837,404	-937,389	-211,508	-243,066	-1.1%
MILK**	2,910,298	287,662	-2,630,021	-2,821,655	-1,794,292	-4,048,007	-23.9%
WOOD***	51,085	7,736	8,074	4,721	3,298	74,915	184.0%
BEEF****	87,394	-20,551	-87,393	-63,341	-101,954	-185,845	-5.6%
OTHER FOR.*	0	-13,403	0	24	-430	-13,809	-1.6%
* quantities in tonnes							
** quantities in thousand liters							
*** quantities in thousand cubic meters							
**** in livestock							

The impacts summarized above are also calculated by municipality. The geographical distribution of the total impacts, scaled by production, can be accessed in Appendix A.3.5 for scenario B2 (Figure A.3.2).

The next table reviews the results in monetary values of 2011. The effects are calculated using the average expected prices used in the estimations by regions (adjusted by the IPCA and converted to dollars).⁷⁶

The most impacted product is maize, as it is an important crop in terms of production, followed by coffee and beef production. As the above tables suggested, soybeans are on average positively affected by climate changes.

⁷⁶ The IPCA is the national consumer price index. The exchange rate (average between buy and sell rates) in 2011 was R\$ 1.8755/US\$. Source: Sisbacen PTAX800.

If only the negatively affected products are counted, the total loss varies from 20.2 to 22.2 billion dollars (2040-2069, B2 and A2 respectively) and 29.5 to 40 billion dollars (2070-2099, B2 and A2 respectively).

Table 3.14: Expected loss/gain in thousand dollars, by product.

Total impact (in thousand US\$)	2070-2099		2040-2069	
	A2	B2	A2	B2
SOYBEANS	18,356,391	7,800,817	7,492,002	5,797,190
MAIZE	-32,405,954	-21,173,862	-16,616,423	-13,391,211
OTHER ANNUAL.	2,856,792	-468,878	1,449,614	1,414,939
COFFEE	-4,303,034	-4,374,969	-2,721,208	-2,758,696
OTHER PEREN.	2,483,300	-371,177	-717,465	-1,730,494
MILK	6,833,588	-1,331,718	2,492,212	-707,374
WOOD	865,875	676,169	673,609	715,158
BEEF	-3,657,008	-2,248,954	-2,128,847	-1,619,200
OTHER FOR.	-11,812	-12,157	-7,045	-12,700
Total	-8,981,861	-21,504,728	-10,083,551	-12,292,387
% of Agric. GDP*	-8.7%	-20.9%	-9.8%	-12.0%

* The 2011 agricultural Gross Domestic Product (GDP) for Brazil was R\$ 192.7 billion, or US\$ 102.7 billion (IBGE).

The balance of gains and losses indicates net losses of 9.8 to 12% for 2040-2069 and 8.7 to 21% for 2070-2099 in terms of the agricultural GDP in 2011. The same impacts calculated by region (summing up the losses in dollars) generate the following information:

Table 3.15: Expected loss/gain in thousand dollars, by region.

Total impact (in thousand US\$)	2070-2099		2040-2069	
	A2	B2	A2	B2
North	4,099,362	3,080,740	1,871,070	984,517
Northeast	3,600,090	-6,703,599	-6,069,200	-5,103,463
Southeast	-9,218,995	-11,303,049	-6,653,777	-6,758,171
South	25,330,504	15,699,132	18,422,657	14,130,940
Midwest	-32,792,822	-22,277,952	-17,654,301	-15,546,211
Total	-8,981,861	-21,504,728	-10,083,551	-12,292,387

The results from this chapter indicate the Midwest, Northeast (except for scenario A2 for 2070-2099), and Southeast regions as the most vulnerable areas if future changes in temperature occur as expected. The South and North regions might expect positive effects from possible climate changes, in general. These results are in accordance with

the literature. The first Brazilian studies that estimated the effects of climate change on agricultural activity using the Ricardian approach found that the Northeast and Midwest regions would be the most affected (SANGHI *et al.*, 1997; SIQUEIRA *et al.*, 1995). Evenson and Alves (1998) found similar results for the most affected areas: the Northeast, Midwest and North regions. In relation to the South and Southeast regions, the authors found that they might be positively affected by changes in precipitation and temperature. Those results are similar to the ones found by Féres *et al.* (2008), who applied the same Ricardian approach with the fixed-effects correction proposed by Deschênes and Greenstone (2007).

3.5.4 Compensation measures for expected climate change

The adaptation measures needed to offset the expected negative effects of climate change on agricultural production might come from some of the technological variables included in the model.

To perform the calculations and test the importance of such variables to compensate potential harmful effects of climate change, it is assumed that the exogenous variables matrix of equation 3.4 can be divided into $Z = (Z^1, Z^2, Z^3)$; where Z^1 represents the vector of climate variables, Z^2 represents the vector of technological variables, and (Z^3) represents other quasi-fixed inputs. The previous sections calculated the effect of Z^1 on each product's output (j): $\frac{\partial \ln(q_j)}{\partial Z^1}$, which is the semi-elasticity estimated (marginal impact of average climate on the % of output j 's production). Algebraically, the effect of the statistically significant Z^2 variable on production can be also estimated by calculating the semi-elasticity:

$$\frac{\partial \ln(q_j)}{\partial Z^2} = \frac{\partial q_j}{\partial Z^2} \frac{1}{q_j} \quad (3.17)$$

Hence, one way to estimate the compensation measure to offset the expected harmful climate change effects is to assume that the loss in production caused by climate change must be equivalent to the gain in production from the increase in technology (assuming that t is future time, and $t = 0$ is current time):

$$\frac{\partial q_j}{\partial Z^1} \Delta Z_t^1 = \frac{\partial q_j}{\partial Z^2} \Delta Z_t^2 \quad (3.18)$$

Thus, the measure ΔZ_t^2 indicates the amount of technology that might compensate the loss from the negative effects of expected climate change (ΔZ_t^1). The idea is that the long-term climate adaptation measures can be calculated by the production loss compensation of using more technology to mitigate the harmful effects of climate change.

An important caveat must be made: both sides of equation 3.18 are partial effects. Thus, the climate change effect is calculated by assuming that technological variables are given and technological effects are estimated by considering all other variables fixed. Despite the fact that this exercise does not study both variables changing together, it provides useful information regarding the ways of compensating the expected changes in future climate.

The calculations are performed by municipality and only statistically significant effects for the technological variables are used to calculate the compensations. Moreover, only negative effects of climate change are considered by municipality (positive effects were disregarded). Next table shows the compensation measures calculated for the following variables: mechanical harvesting; cattle confinement; irrigated area; tilled area; and transgenic or certified seeds.

Table 3.16: Variation in the technological variables (ΔZ_t^2) that compensate expected climate change losses in production, by scenario and forecast period.

Adaptation measures (ΔZ_t^2 in %)	Mechanical harvesting	Confined cattle	Irrigated area	Tilled area	Transgenic or certified seeds
Scenario B2 (2040-2069)					
beef	47.3%	25.2%	9.5%	75.8%	<i>n.s.</i>
coffee	2.2%	2.8%	0.7%	1.9%	4.9%
milk	8.8%	3.4%	2.2%	2.6%	11.1%
maize	6.0%	3.4%	9.1%	44.6%	5.8%
other for	<i>n.s.</i>	6.2%	1.5%	4.8%	5.8%
other peren.	1.5%	5.4%	0.7%	6.8%	5.5%
other annual	12.7%	10.3%	1.5%	11.8%	10.3%
soybeans	27.4%	30.8%	18.0%	55.8%	131.3%
wood	<i>n.s.</i>	<i>n.s.</i>	0.3%	<i>n.s.</i>	3.6%
Scenario B2 (2070-2099)					
beef	82.2%	36.9%	14.3%	46.0%	<i>n.s.</i>
coffee	4.8%	5.7%	1.3%	2.2%	4.2%
milk	10.6%	5.9%	3.6%	3.1%	16.7%
maize	17.6%	4.0%	7.4%	65.8%	13.7%

Adaptation measures (ΔZ_t^2 in %)	Mechanical harvesting	Confined cattle	Irrigated area	Tilled area	Transgenic or certified seeds
Scenario B2 (2070-2099) cont.					
other for	3.1%	9.8%	0.9%	5.3%	3.2%
other peren.	2.0%	6.2%	0.7%	8.5%	9.5%
other annual	14.1%	14.2%	2.0%	17.6%	14.9%
soybeans	36.9%	40.6%	23.4%	53.8%	219.9%
wood	<i>n.s.</i>	<i>n.s.</i>	0.3%	<i>n.s.</i>	3.7%
Scenario A2 (2040-2069)					
beef	67.5%	33.8%	13.1%	86.7%	<i>n.s.</i>
coffee	4.3%	2.5%	0.6%	4.1%	6.0%
milk	9.3%	4.6%	2.5%	3.2%	12.2%
maize	4.8%	3.9%	7.4%	55.5%	4.7%
other for	4.6%	10.8%	2.0%	5.9%	3.9%
other peren.	1.6%	6.3%	0.6%	6.4%	6.6%
other annual	14.5%	14.0%	1.9%	14.1%	12.4%
soybeans	34.5%	36.5%	21.3%	65.2%	159.6%
wood	<i>n.s.</i>	<i>n.s.</i>	0.3%	<i>n.s.</i>	2.8%
Scenario A2 (2070-2099)					
beef	122.3%	57.7%	22.3%	79.8%	<i>n.s.</i>
coffee	7.5%	5.7%	1.0%	4.9%	10.7%
milk	21.3%	7.6%	4.8%	6.3%	25.0%
maize	24.9%	5.7%	5.2%	100.3%	16.9%
other for	<i>n.s.</i>	16.2%	2.8%	12.9%	13.3%
other peren.	3.0%	8.7%	1.0%	9.2%	14.5%
other annual	27.6%	20.6%	3.3%	23.5%	20.8%
soybeans	58.9%	70.2%	40.2%	86.8%	315.5%
wood	<i>n.s.</i>	<i>n.s.</i>	0.4%	<i>n.s.</i>	4.2%

n.s. not statistically significant at 10%

In general, irrigation seems to be the most important compensation measure, as the results suggest that small increases in the irrigated area might be sufficient to compensate the expected future climate changes. However, as the descriptive data show, the average irrigated area in the country is very low, since irrigation techniques are expensive. Some studies have already pointed to irrigation as the major adaptation measure in Latin America (CUNHA *et al.*, 2012; SEO, 2011; Margulis and Dubeux, 2010).

In terms of smaller increases to compensate climate changes, some other variables might be important adaptation measures:

- An increase of 5% to 15% in transgenic or certified seed usage might be important adaptation measures for coffee, milk, maize, other forest products, other perennial crops, other annual crops and wood for most of the scenarios analyzed;
- An increase in mechanical harvesting in Brazil might also help farmers to adapt and nullify the expected effects from climate change for the following products: coffee; milk; maize; other annual and other perennial crops;
- Confining cattle can be used to offset losses in production of beef (second-best alternative), milk, maize, coffee and other perennial crops;
- In regard to increase of tilled area, the best results are found for coffee, milk, other forest products, and other annual and perennial crops.

The best comparison of the techniques must take into account the cost of such procedures. The table above only shows the potential benefits that each technique might generate to offset the expected effects of climate change. Margulis and Dubeux (2010) estimate the cost-benefit for irrigation and genetic improvement and find out that irrigation might be the best compensation measure for maize, while genetic improvement is more cost-effective for coffee.

Few studies have not considered technological influences in their projections of climate change effects on agriculture. Nadal (2010) is one of the first studies for Brazil that considers investments to measure compensations to expected climate changes. Nevertheless, only some types of crops, mainly annual ones, are considered in her analysis, which does not take into account many perennial crops, cattle ranching and forest products. Thus, the impacts of climate change on agricultural activity are minimized.

3.6 Conclusion

This chapter bases its development on the hypothesis that climate is a direct input for crop and animal production, which means that farmers observe local average climate and make allocative decisions taking this information into account. Thus, by using a translog profit frontier equation and data from the Agricultural Census of 2006, the following steps are carried out: i) the average climate relevance on farmers' outcomes is tested; ii) once average climate is identified as relevant, average climate marginal effects on production are calculated by product; iii) using CPTEC/INPE forecasts for

climate changes in Brazil by microrregions, the possible loss/gain in production is calculated; and iv) from the expected losses from climate changes, the compensation measures are calculated by technological variables, which can be interpreted as potential adaptation measures for climate changes.

The marginal temperature effects calculated seem to be much higher than the precipitation ones. The partial effects of higher average summer temperature reduce production of maize, other annual crops, coffee, other perennial crops, milk and beef. Places with higher winter temperatures might suffer adverse effect on coffee and soybean output. Only soybean production is affected positively by higher summer temperatures. One possible explanation is the current high adaptability of this crop, which may have influenced the results.

The balance of gains and losses from expected climate changes indicates net losses of between 9.8 and 12% for 2040-2069 and 8.7 and 21% for 2070-2099 in terms of agricultural GDP of 2011. The results also suggest that more damage is expected from climate change in the Midwest, Northeast and Southeast regions. On the other hand, the South and North regions can expect positive general effects from climate changes. These results are in accordance with the literature.

By using the mentioned expected climate change results, compensation measures are calculated and, in general, irrigation seems to be the most important compensation technique. Other measures can be more important to some products than other, such as transgenic and certified seeds for crops in general, cattle confinement for potential milk and beef losses, mechanical harvesting for maize and other annual crops, and tilled area for coffee and other annual and perennial crops.

Those measures can be interpreted as adaptation strategies to expected climate change impacts on agriculture. However, there are many costs and barriers that were not taken into account in this study (such as investment and opportunity cost comparisons). On the other hand, this is the first exercise that includes many different technologies inside an economic modeling approach for agriculture, considering almost all the agricultural products of the economy.

4. EXTREME WEATHER EVENTS' IMPACT ON AGRICULTURE

4.1 Introduction

Changes in the average climate conditions are assumed to reflect climate change, making them exogenous to the farmer decisions. In the previous chapter they are considered direct fixed inputs in the model. However, another important climate influence on agriculture is related to the specific weather conditions during the growing and harvest seasons, which are not observed by farmers during their decision-making process – namely: short-term climate conditions.

In general, the negative effects of short-term climate on agriculture are related to the extreme weather events that affect agriculture through crop failure or changes in crop or animal productivity, caused by droughts, frosts, hail, severe storms and floods, among others. During the summer of 2012, for example, the governments of Rio Grande do Sul and Santa Catarina states, in Brazil, calculated that the agricultural losses due to droughts reached US\$ 480 million for maize, dairy products and beans. During the same period it is estimated that soybean production in South America fell 3% below the expected level due to adverse weather.⁷⁷

Extreme weather events also contribute indirectly to the existence of rural poverty. According to Rosenzweig and Wolpin (1993), poor (normally small) farmers avoid taking risks or spending assets, by obtaining larger loans or contracting insurance, under the threat of extreme weather events, which limits their productivity gains through investment in capital and innovations. Poor farmers do not completely utilize their important assets: they save them for crisis survival. This behavior has been pointed out as a possible reason impeding growth of small farmers, working as well to maintain or even increase inequality in agriculture. Rosenzweig and Biswanger (1993) also suggest that uninsured weather risks can result in lower efficiency and lower profits for small farmers.

⁷⁷ See Valor Econômico (2012).

With these concerns in mind, the following questions are addressed to understand how extreme weather events impact profitability and efficiency of farmers in Brazil:

- I) Do extreme weather events divert Brazilian farmers from their optimal outcome?
- II) What is the estimated magnitude of damages caused by extreme weather events?
- III) How can farmers deal with extreme weather events?

To respond to these questions, it is crucial to identify the factors leading to production failures (inefficiencies) in agriculture, which is assumed to be measured by a technical efficiency (TE) ratio that captures farmers' failure to meet the expected production plan (BERGER *et al.*, 1993).

This chapter uses TE as an indicator of deviations of farmers from optimal profit and tests its statistical significance. It also attempts to pinpoint factors explaining these deviations. The important argument in favor of this analysis is that it identifies variations of the physical/financial performance achieved by farmers operating under the same environmental and economic conditions.

To illustrate this idea, suppose that two identical farmers grow maize⁷⁸, one located in the north of Rio Grande do Sul and the other in the south of Paraná (both in the south of Brazil). Factor proportion is equal and average climate conditions are practically the same for both farmers. Thus, one question that arises is: What would explain observed differences in production, and in profits, between the farmers?

One explanation could be the ability of one farmer to produce maize, because of having received some specific training or having more experience. However, if the farmers have identical attributes, the occurrence of an extreme weather event in the region of farmer 1 (and not in the region of farmer 2), for example, could generate a difference in agricultural performance between the two farmers, given that the inputs used and other conditions are the same for both. This event is unpredictable by the farmer and, consequently, is out of his control.

The above example illustrates that many factors, including short-term climate, can contribute to the difference in farmers' efficiency in generating outcomes and the recognition of such contributions is relevant to plan actions to improve farmers'

⁷⁸ Suppose that farmers and farms are identical, in terms of area, soil quality and input usage, among others.

performance. The analysis in this chapter is an attempt to identify these factors, focusing on the specific contribution of extreme weather events to farm losses.

Since the short-term weather effects are statistically significant to explain TE, two different analyses follow: I) estimation of total loss of profits caused by extreme weather events, as a proxy of farmers' maximum willingness to pay to prevent being harmed by unforeseen drastic weather changes; II) analysis of the actions that might reduce farmers' weather losses due to extreme deviations from normal weather patterns.

The organization of the chapter is as follows: Section 4.2 reviews the profit frontier approach from which a TE indicator for producers is derived. A review of the literature on TE determinants is also carried out to show how this study relates to the empirical literature in this area. The following section describes the data used in the analysis. Section 4.4 presents the results and the final section comments on the findings.

4.2 Profit frontier and technical determinants

This section briefly summarizes the profit frontier model described in Chapter 3. Subsequently, it explains how the TE is estimated based on the profit frontier parameters, followed by a review of the literature on the determinants of this efficiency measure.

4.2.1 Profit frontier approach: Review

The profit function is obtained by replacing farmers' optimal allocation of inputs and outputs inside a short-run profit function (or restricted profit function), given an endowment of fixed factors (fixed in the short run), and prices⁷⁹. Therefore, the profit function depends on the exogenous variables: prices; and other quasi-fixed inputs. This approach assumes that agricultural markets are perfect, implying that farmers are fully efficient in optimizing profit.

Kumbhakar and Lovel (2000) emphasizes that not all producers are efficient. Based on a dual profit frontier approach, producers operating on their profit frontier are profit efficient, while producers operating beneath are labeled profit inefficient. The next figure, reproduced from their book, illustrates the notion of profit inefficiency:

⁷⁹ See Chapter 3 for more details.

Figure 4.1: Measurement of profit inefficiency

Source: Prepared by the author based on Kumbhakar and Lovell (2000).

In the figure above, the producer facing relative prices $(w/p)^A$ achieves maximum efficiency (maximum profits) at output-input combination **E**, but incurs inefficiency for all other feasible input-output combinations inside the gray area, such as **F**: (x^A, y^A) , and on the production function frontier (except for **E**), such as **G**: $(x^A, \rho y^A)$. This inefficiency can be divided into: technical inefficiency (**F** to **G**), where the farmer is using an input-output combination outside the production frontier and the term ρy^A assumes a radial expansion of the initial output (y^A) in order to achieve the frontier; and allocative inefficiency (**G** to **E**), where farmers do not envision the right relative prices when deciding on the amount of inputs and outputs, making them choose the wrong input-output mix.

However, assuming that the correct relative market prices $(w/p)^A$ are observed by the farmers, all the inefficiency of **F** comes from technical issues. Hence, the difference between **F** and **E** can be considered technical inefficiency.

The efficiency analysis, as a result, helps to identify variations of the physical and financial performance achieved by farmers operating under the same conditions. Thus, Kumbhakar and Lovell (2000) argued that by relaxing the assumption of full efficiency, a profit (or technical) efficiency measure can be described as the ratio of the actual profit in terms of the potential maximum profit.

What underlies the existence of deviations from the full efficiency is that the inefficient farmers can survive in the short run. Two main reasons can explain the existence of

technical inefficiency: producers do not achieve the maximum profit because they produce less of an output; or because they use more of an input than a hypothetically fully efficient producer (BERGER *et al.*, 1993).

Considering the potential inefficiencies (τ)⁸⁰ in the profit function and assuming the transcendental logarithm (translog) function for farmers' restricted profit function (CHRISTENSEN *et al.*, 1975),⁸¹ the translog profit frontier normalized at netput 1, described in Chapter 3,⁸² is:

$$\begin{aligned} \ln\left(\frac{\Pi}{p_1}\right) = & \beta_0 + \sum_{j>1} \beta_j \ln(p_j/p_1) + \frac{1}{2} \sum_{j>1} \sum_{k>1} \beta_{jk} \ln(p_j/p_1) \ln(p_k/p_1) \\ & + \sum_{j>1} \sum_{r=1}^f \gamma_{jr} Z_{jr} \ln(p_j/p_1) + \sum_{r=1}^f \delta_r Z_r \\ & + \frac{1}{2} \sum_{h=1}^f \sum_{r=1}^f \theta_{hr} Z_h Z_r - \tau \end{aligned} \quad (4.1)$$

In which $j, k = 1, \dots, m$; $r, h = 1, \dots, f$; and $\beta, \delta, \theta, \gamma$, and τ are parameter vectors;

m is the total products considered, $m = g + s$ (s outputs and g inputs);

Π denotes the profit;

$p = (p_1, \dots, p_m)'$ denotes the exogenous prices (farmers are price-takers);

and $Z = (Z_1, \dots, Z_f)'$ is the vector of quasi-fixed inputs.

Note that τ measures the shifts of profit away from the optimum (namely Π^*) or the failure of the farmer to reach the maximum possible profit:

$$\tau = \ln \Pi^*(p, Z) - \ln \Pi, j=1, 2, \dots, m \quad (4.2)$$

In which Π is the actual profit level achieved, and $\tau \geq 0$ is the inefficiency term for both the underproduction of outputs and overuse of inputs. This measure can be interpreted as the intrinsic total profit/technical inefficiency of each farmer. Thus, the TE ratio is characterized by the loss of profits from not producing the desired levels and is obtained by comparing both optimal and achieved profits:

⁸⁰ The technical inefficiency measure, as Berger *et al.* (1993) point out, might also include idiosyncratic factors not included in the model (input quality, for example). This study assumes no correlation between these factors and the exogenous variables for the profit function, which generates consistent estimation.

⁸¹ It is assumed that there are no allocative inefficiencies.

⁸² Chapter 3 explains the importance of the theoretical assumptions that guarantee the consistency of farmers' choices to reach the optimal solution just described.

$$TE = \exp(-\tau) = \frac{\Pi(p, Z)}{\Pi^*(p, Z)} \quad (4.3)$$

As $\tau \geq 0$, the measure of TE varies from zero (least efficient) to the unity (fully-efficient). The next section explains the statistical tools used to estimate the parameter τ and, consequently, to generate the estimates of TE.

4.2.2 Empirical strategy: TE estimation

Appendix A.3.4 shows the conditions to estimate the profit frontier model by deriving the probability density function (pdf) of the composed error of equation A.3.14: $y_i = -\tau_i + v_i$ (KUMBHAKAR; LOVELL, 2000). By assuming that $v_i \sim iidN(0, \sigma_v)$, $\tau_i \sim iidN^+(\mu, \sigma_\mu)$ ⁸³ and τ_i and v_i are distributed independently of the covariates of the profit function, the pdf of the composed error (y) can be derived, and consequently the log-likelihood function of this error term can be obtained. Assuming independence among the observations, the log-likelihood estimation method is implemented using Stata to obtain the estimated parameter values that maximize the ML which are the estimated coefficients of the profit frontier.

According to Kumbhakar and Lovell (2000), the estimation of τ_i , and consequently of TE_i , requires derivation of the conditional distribution of τ_i on y_i , $f(\tau_i/y_i)$, which is a normal distribution with mean $\tilde{\mu}_i$ and variance $\tilde{\sigma}^2$, such that:

$$\tilde{\mu}_i = (-\sigma_u^2 y_i + \mu \sigma_v^2) / \sigma \quad (4.4)$$

and

$$\tilde{\sigma}^2 = \sigma_u^2 \sigma_v^2 / \sigma^2 \quad (4.5)$$

In which: $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$.

Thus, the conditional mean $E(\tau_i/y_i)$ can be an estimate of τ_i and can then be replaced in equation 4.3 to estimate TE:

$$\widehat{TE}_i = E[\exp(-\tau_i)/y_i] = \frac{1 - \Phi(\tilde{\sigma} - \tilde{\mu}_i/\tilde{\sigma})}{1 - \Phi(-\tilde{\mu}_i/\tilde{\sigma})} \exp(-\tilde{\mu}_i + 1/2 \cdot \tilde{\sigma}^2) \quad (4.7)$$

In which $\Phi(\cdot)$ is the normal cumulative distribution function. Kumbhakar and Lovell

⁸³ This thesis considered the positive normal truncated distribution. However, as Kumbhakar and Lovell (2000) emphasizes, the choice between exponential, half-normal and truncated normal does not change much the results estimated.

(2000) present this procedure, showing that it generates unbiased estimators for TE.

After valuing TE, the second step is to estimate the TE determinants, which will be discussed further. In order to generate unbiased TE estimators, the determinants should be uncorrelated with the covariates of the profit function, an assumption considered in this study.

4.2.3 Determinants of TE

The measurement of the TE allows the study of its determinants, which are assumed to impact farmers' deviations from optimum choices. An important study on TE determinants was developed by Battese and Coelli (1995), who state that efficiency can be explained by a set of exogenous variables.⁸⁴ As mentioned, the set of determinants must be exogenous to the farmer's choice. Formally, the technical efficiency determinant equation can be described as:

$$TE_i = f(C_i, X_i, D_i) + \varepsilon_i \quad (4.8)$$

In which:

ε_i is a random shock with positive distribution for each farmer (represented by the representative farmer of municipality i);

C_i is a vector of climate anomalies (extreme weather variables, for example) in the period for municipality i ;

X_i is a vector of farmer characteristics for municipality i ;

and D_i is a vector of other determinants.

The dependent variable is limited to the range of [0,1], implying the use of specific econometric techniques.

According to Gorton and Davidova (2004), the determinants can be divided into two main groups: human capital effects and structural effects. The former group includes information on the farmers' management, their characteristics and education, while the latter group comprises environmental conditions, credit access and information on

⁸⁴ Battese and Coelli (1995) propose a joint estimation between the profit equation and the determinants equation, assuming that the average of τ_i (μ) is a function of those determinants. This procedure eliminates possible inconsistency, as τ_i is assumed to be identically distributed in the profit frontier equation, such as assumed by this analysis.

property rights, among others. The main components of each group are briefly described below. Most of the literature reviewed is summarized in Tables 4.1 and 4.2, for the international and Brazilian literature, respectively.

(i) Environmental conditions: Climate

Kumar (2009) stated that weather deviations from normal conditions can influence crop growth and, consequently, the TE of farmers. The work of Sherlund *et al.* (2002) applied a translog production frontier model to Côte d'Ivoire and found that the exclusion of climate variables in the determinants equation might lead to biased parameters.

Demir and Mahmud (2005) also included environmental factors to explain efficiency differences. They emphasized that the omission of climate variables, under the argument that they are beyond farmers' control, can lead to inaccurate interregional technical efficiency comparisons. By estimating the TE equation from a translog stochastic production frontier function for Turkish farmers, they showed that not only are the agro-climatic variables statistically significant, but also their omission substantially affects mean output elasticities and relative technical efficiencies. They considered anomaly in rainfall (rainfall above or below the national average) as one of the main determinants of technical inefficiency.

In Brazil, Igliori (2005) and Imori (2012) also considered climate in their approach to identify efficiency determinants for the Amazon region and Brazilian farmers, respectively. Igliori found no significance of temperature and rainfall in his model. On the other hand, Imori found statistically significant impacts of temperature and precipitation on the estimated technical efficiency. Imori considered average climate conditions (30-year average) as a determinant of technical efficiency.

(ii) Farm management conditions

According to the literature, the main variables that influence farm management are farmers' socioeconomic circumstances, such as education and farming experience.

Many studies have identified farmer education and characteristics as important determinants of efficiency.⁸⁵ An increase in the level of farmer education, *ceteris paribus*, increases the use of more advanced techniques due to the increased capacity to understand the technical aspects related to agricultural production (ALI *et al.*, 1994; COELLI; FLEMING, 2004). Thus better education can spur the spread of technical change (HUFFMAN; EVENSON, 1989).

Another relevant variable that influences efficiency of farmers is farm size.⁸⁶ Imori (2012) reviews the discussions of its effect on efficiency: in general, the literature points to an inverse relation of size and efficiency, as small farmers might use an exceptional amount of work to compensate the failures of product and credit markets that they observe (difference in risk exposures).⁸⁷

(iii) Other structural determinants

Rural infrastructure is singled out as a key limiting determinant of efficiency by Ahmed and Hossain (1990). Other studies have also identified this influence by calculating the impact of the distance to markets and extension services (BHASIN, 2002), agricultural infrastructure (RAHMAN, 2003), and regional differences (TZOUVELEKAS *et al.*, 2001) on inefficiency.

Soil conditions might also have a positive or negative influence on productivity, as highlighted by Rahman (2005) and Rahman and Parkinson (2007).

Some of the literature also identifies production diversification as a factor that can affect farmers' efficiencies. However, the results achieved by the papers suggest mixed positive and negative effects of crop diversification on technical efficiency (COELLI; FLEMING 2004; LLEWELLYN; WILLIAMS, 1996; RAHMAN, 2009).

Investigating credit constraints, Helfand (2003) and Imori (2012) posit that they can lead to non-optimal choices by farmers, being an important source of inefficiency in agriculture.

⁸⁵ See Xu and Jeffrey (1998), Abdulai and Huffman (1998), Bhasin (2002), Rahman (2003), Kolawole (2006) and Bozoglu and Ceyhan (2006).

⁸⁶ See Ali *et al.* (1994), Ali and Flinn (1989), Wang *et al.* (1996), Xu and Jeffrey (1998) and Tzouvelekas *et al.* (2001).

⁸⁷ See Barret (1996) for the theoretical development of this argument.

The empirical agricultural studies are mostly based on the modeling approach of Battesi and Coelli (1995). Table 4.1 summarizes most of the international literature reviewed above (OZKAN *et al.*, 2009):

Table 4.1: Summary of studies on technical inefficiency determinants, international literature

Paper	Country	Period	Main Results
Xu and Jeffrey (1998)	China	1985-1986	Education and farm size are relevant to explain technical efficiency (production frontier)
Bravo-Ureta and Rieger (1991)	United States	1984	Average technical efficiency of 83%, not correlated with socioeconomic and demographic variables (cost frontier)
Abdulai and Huffman (1998)	Ghana	1992-1993	Profit inefficiency is related to enterprise and household characteristics (profit frontier)
Tzouvelekas, Pantzios, and Fotopoulos (2001)	Greece	1995-1996	Productive efficiency is related to family labor share, farm size, capital stock and regional differences (production frontier)
Wilson et al (2001)	England	1993-1997	Productive efficiency is related to farmers characteristics and management issues (production frontier)
Arnade and Trueblood (2002)	Russia	1994-1995	Calculate the technical and allocative inefficiencies. Results indicate that inefficiencies limits supply responses to prices (profit frontier)
Bhasin (2002)	Ghana	<i>n.i.</i>	Productive efficiency is related to farmer's education and distance to markets and extension services (production frontier)
Kompas, Che and Grafton (2003)	Australia	1990-2000	Technical efficiency decrease after government's regulation on vessel size(production frontier)
Irairoz et al (2003)	Spain	1994	Technical efficiency positively related to productivity indexes (nonparametric method - DEA)
Rahman (2003)	Bangladesh	1996	Technical inefficiency is related to agricultural infrastructure, farmer's experience and service extension (profit frontier)
Kolawole (2006)	Nigeria	<i>n.i.</i>	Technical inefficiency is related to farmer's characteristics and profit efficiency calculated was 60% (profit frontier)
Demir and Mahmud (2005)	Turkey	1993-1995	Production frontier methodology considering agro-climatic and environmental factors in production function. The omission of these variables can cause bias in elasticities and technical efficiency estimated
Bozoglu and Ceyhan (2006)	Turkey	2002-2003	Profit frontier analysis. Technical Efficiency determinants are farmer's education, experience, credit use opportunities, and women participation in labor force

n.i. No information in the paper

In general, the results of the determinants of efficiency have shown no systematic differences between the stochastic production function and stochastic profit frontier studies. However, production frontier approaches are more used when the sample of

farmers is not very heterogeneous. Most of the resulting differences are due to the distinct specifications among the studies in terms of exogenous variables included.

A similar comparison for the Brazilian empirical literature is summarized in Table 4.2. All Brazilian studies analyzed used stochastic production frontier or data envelopment analysis (DEA), which is a deterministic approach for the production function.

Table 4.2: Summary of studies on technical inefficiency determinants, Brazilian literature

Paper	Region	Period	Main Results
Taylor e Shonkwiler (1986)	Zona da Mata region ⁸⁸	1981-82	Production frontier method to evaluate a credit program (PRODEMATA), which is shown to have positively affected participant farmers.
Helfand and Levine (2004)	Midwest region	1996	Nonlinear relationship between technical efficiency and farm size, land tenants more efficient (DEA model).
Iglioni (2005)	Brazilian Amazon	1970-2000	Technical inefficiency is related to environmental conditions, location, transportation network, farm size distribution, and the size of local economies (production frontier).
Nogueira (2005)	Brazil	1996	Positive effects related to efficiency: technical assistance, electricity; negative relationship: pest control; rural education program (DEA model).
Magalhães <i>et al.</i> (2011)	North region	2002-03	Technical inefficiency negatively affected by the self-consumption of production (Cobb-Douglas production function).
Imori (2012)	Brazil	2006	Family agriculture less efficient, formally educated farmers and credit access lead to more efficiency, among other factors (production frontier).

4.3 Data sources and description

Most of the variables for the modeling of this chapter are from the Brazilian Agricultural Census of 2006.⁸⁹ Once the TE component is estimated, a group of

⁸⁸ PRODEMATA: Integrated Development Program of the Zona da Mata. The Zona da Mata ("Forest Zone") is a sub-region of the northeast coastal area of Brazil that extends from the state of Rio Grande do Norte to the south of Bahia.

variables identified by the literature as potential explanatory factors for TE, limited by data availability, is selected. These variables, except for climate, are described below:

- *Farmer education and experience*: the available information is the percentage of population that completed each level of education (none or incomplete elementary, complete elementary, incomplete high school, complete high school, and higher education)⁹⁰, and the percentage of farmers who run establishments by years of experience: less than 1 year, 1-5 years, 5-10 years, over 10 years;
- *Other farmer characteristics*: percentage of female farmers, percentage of farmers who own their land, percentage of tenants/sharecroppers;
- *Soil type*: percentage of degraded land in the municipality out of the total area;
- *Farm size*: average size of farms in the municipality, calculated by hectares per establishment; and percentage of family farms in the municipality;
- *Production diversification*: the general Herfindahl-Hirschman Index (HHI) is calculated based on the value of production among the following aggregated products: large animals, midsize animals, small animals, perennial crops, annual crops, horticulture, forestry and plant extraction. The index represents agricultural diversification and/or concentration. A zero value denotes perfect diversification and a value of 1 denotes perfect specialization;
- *Access to credit*: Percentage of establishments that obtained some type of loan from different sources (banks, cooperatives, among others);
- *Altitude*: Altitude in meters, which is believed to increase the risk of frosts⁹¹ (the data were obtained from the IBGE database of cities and towns of 1998);
- *Infrastructure*: Index for logistic cost to São Paulo in 1995, updated in 2009, based on the transportation costs to São Paulo municipality, whose costs are a result of applying a linear programming procedure for calculating the minimum shipping cost to São Paulo (NEMESIS, 2009);
- *Membership in cooperatives*: Producer is a member of a cooperative, union or other similar association;
- *Pest control*: Percentage of agricultural establishments that perform pest control (biocontrol, burning waste, use of repellents, among others).

⁸⁹ The data on agricultural products' quantities and prices in the Agricultural Census of 2006 are used to estimate the profit frontier and, consequently, to estimate the technical efficiency component, according to the method previously discussed.

⁹⁰ For educational variable, the data source is the Demographic Census of 2010, from the IBGE.

⁹¹ Astolpho *et al.* (2005).

When it comes to short-term climate data, the 2005 and 2006 climate information by season (*climate*) is demeaned by the long-term climate data (30-year average, $E(\text{climate})$) and this deviation from long-term mean is divided by the standard deviation, calculated from the former 30-year climate (σ_{climate}), to standardize the climate information. Hence the new variable can be interpreted as climate anomaly or extreme weather intensity. Therefore, four subsets of indexes are created to test their impact on TE and, consequently, on profits:

- Drought Index: Observed rainfall below the long-term average rainfall in standard deviations: $Z_D < E(\text{Rain}) - \alpha\sigma_{\text{Rain}}$;
- Flood Index: Observed rainfall above the long-term average rainfall in standard deviations: $Z_F > E(\text{Rain}) + \alpha\sigma_{\text{Rain}}$;
- Cold Stress Index⁹²: Observed air temperature below the long-term average in standard deviations: $Z_C < E(\text{Temp}) - \alpha\sigma_{\text{Temp}}$; and
- Heat Stress Index: Observed air temperature above the long-term average in standard deviations: $Z_H > E(\text{Temp}) + \alpha\sigma_{\text{Temp}}$.

In this formulation, α represents the intensity of the extreme weather occurrence and all climate variables are transformed in terms of α . These indexes are used after testing the significance of the climate variables in the TE determinants equation, in order to simulate extreme weather events' effects on agriculture.

4.3.1 Descriptive statistics

Table 4.3 describes the dataset discussed previously, except for the climate variables. On average, 24.5% of the farmers in a municipality are members of some kind of association or cooperative. However, the variation calculated from the standard deviation shows that this distribution is very unequal.

⁹² Frosts occur when there is ice deposition on external plants and objects. The occurrence of frosts is due to a combination of low temperatures and moisture in the atmosphere (Pereira *et al.*, 2002, apud CPTEC/INPE, 2011). Frost may cause death of plants when it entails the freezing of plant parts. Some specialists believe that between 0°C and -4°C may be the critical temperatures for more resistant plants, such as coffee, sugarcane and some fruits (MOTA, 1981). Temperatures above this range may cause even worse effects. Normally frosts are worse in the winter and at medium and high latitudes and on higher altitudes areas, mainly the south of Brazil and some higher areas in São Paulo and Minas Gerais states.

With regard to ownership of land, approximately 80% of farmers are the owners of their land, while 4.5% lease the land where they produce. The percentage of degraded land, on average, is small (0.3%) and the maximum degraded area is 48% of total land. A low percentage of farms use some kind of pest control on average, which indicates that many farmers are also subject to deviations from optimal profits due to pests.

Regarding farmer characteristics, most of them are men and the majority has more than 10 years of experience. When it comes to the school structure of the municipalities, this information was collected from the demographic census and indicates that most of the population are illiterate or did not complete elementary school (63.3%), while 4.2% have at least some university education.

Approximately 18% of farmers use some type of credit, which is a low average. The average farm size is 34.2 hectares and the amplitude and high standard deviation of this variable indicate the inequality in size distribution among farms.

The production diversification in the municipality, the mentioned HHI, varies from total diversification (0) to full specialization (1). The average is high, probably because the group of products was aggregated before calculating the HHI. However, the measure is an important indicator of diversification among different agricultural products. The more specialized regions are the Midwest (average of 0.54) and Southeast and South (0.472 and 0.473, respectively).

Table 4.3: Descriptive statistics, 2006 Census

Variable	Obs	Mean	Std. Deviation	Min.	Max.
% of farmers in cooperatives or assoc.	5547	0.245	0.201	0.00	1.00
% of farmers that own the land	5547	0.798	0.180	0.00	1.00
% of tenant farmers	5547	0.045	0.064	0.00	1.00
% of farms that use pest control	5547	0.113	0.134	0.00	1.00
% of pop. with 0 to 4 years of schooling	5548	63.314	9.812	26.00	90.62
% of pop. with 5 to 8 years of schooling	5548	15.653	3.113	4.33	35.13
% of pop. with 9 to 11 years of schooling	5548	16.433	5.583	1.52	40.88
% of pop. > 12 years of schooling	5548	4.169	2.613	0.18	26.69
% of pop. with undetermined schooling	5548	0.431	0.516	0.00	6.48
% of farmers that used any credit	5547	0.180	0.144	0.00	0.85
Altitude of the municipality	5499	412.310	293.070	0.00	1628.00
Average size of farms (in hectares)	5543	34.343	79.918	0.00	1561.98
Agricultural HHI	5546	0.462	0.210	0.00	1.00
% of female farmers	5547	10.977	6.349	0.00	100.00
% of farmers 1 to 5 years of experience	5547	17.995	8.196	0.00	100.00
% of farmers 5 to 10 years of experience	5547	18.539	8.002	0.00	100.00
% of farmers: > 10 years of experience	5547	60.485	13.735	0.00	100.00
% of family farms	5547	78.568	15.424	0.00	100.00
Index for logistic cost to São Paulo	5547	0.299	3.381	0.00	100.00
Degraded agricultural area (in hectares)	5543	0.003	0.010	0.00	0.48

When it comes to the TE in 2006, the null hypothesis of no inefficient component is rejected by the data.⁹³ The histogram of the technical efficiency estimated is illustrated next.

⁹³ The statistic of the z-test is 94.89 (with a p-value of 0.000), rejecting the null hypothesis of full efficiency. The test is based on Coelli (1995), who noticed that the presence of an inefficiency term would negatively skew the residuals from an OLS regression, so the author proposed a test in the third moment of the compound error distribution.

Figure 4.2: Estimated technical efficiency measure, municipalities in 2006.

The mean of this distribution is 51.3%. Approximately half of the municipalities where the efficiency is calculated have TE between 0.43 and 0.63. The highest efficiency measured is 0.87. Figure 4.3, below, shows the percentage of farmers presenting TE above the average for the country.

Figure 4.3: Percentage of municipalities above the average (51.3%), by state, 2006

The states with the greatest number of municipalities above the average are: Acre and Rondônia in the North region; Rio Grande do Sul and Paraná in the South; Espírito Santo in the Southeast; and Bahia, Sergipe, Alagoas and Ceará in the Northeast.

Many of the Brazilian states where agriculture is very intensive, such as São Paulo, Minas Gerais, Mato Grosso and Goiás, presented 40 to 60% of the municipalities above the average. The less efficient municipalities are more prevalent in Tocantins, Roraima, Rio Grande do Norte and Mato Grosso do Sul.

4.3.2 Climate description: 2005-2006

Table 4.4 below summarizes the climate information on municipal weather in 2005 and 2006. This information is also mapped and the figures are illustrated in Appendix A.4.1.

Table 4.4: Descriptive statistics, rainfall and temperature deviations from long-term average, 2005 and 2006, by region

Variable (average)	North	Northeast	Southeast	South	Midwest	Brazil
Rainfall: $[Z_i^{Rain} - E(Rain)] / \sigma_{Rain}$						
Summer (2006)	0.226	-0.406	-0.135	-0.519	0.184	-0.249
Fall (2006)	0.620	0.448	0.093	-0.455	0.250	0.146
Winter (2006)	0.048	-0.043	-0.381	-0.230	-0.375	-0.204
Spring (2006)	0.200	0.337	0.503	0.057	0.421	0.323
Summer (2005)	-0.213	-0.358	0.285	-0.705	-0.119	-0.209
Fall (2005)	0.127	0.029	0.314	0.574	0.122	0.246
Winter (2005)	-0.328	0.175	0.074	0.327	-0.375	0.091
Spring (2005)	-0.315	-0.583	0.351	0.666	0.139	0.045
Temperature: $[Z_i^{Temp} - E(Temp)] / \sigma_{Temp}$						
Summer (2006)	0.792	0.751	0.372	0.543	0.659	0.589
Fall (2006)	0.134	0.157	-0.115	-0.243	-0.034	-0.028
Winter (2006)	0.868	-0.018	0.273	0.678	0.811	0.359
Spring (2006)	0.993	0.370	0.019	0.149	0.411	0.272
Summer (2005)	1.429	0.950	0.130	0.415	1.121	0.644
Fall (2005)	1.131	0.644	0.402	0.323	0.662	0.544
Winter (2005)	1.193	0.299	0.472	0.625	0.795	0.534
Spring (2005)	1.362	0.724	0.400	-0.141	0.943	0.513

The mean of the rainfall deviation from average conditions by region suggests there were many drier seasons than expected in the period. The South region was the most affected by lack of rainfall, mainly in 2006 and in the summer of 2005 to 2006. The Northeast region was also affected by drier seasons. The only regions receiving larger precipitation than average were the North in 2006 and the Southeast in 2005.

The figures in Appendix A.4.1 suggest that the Amazon region also suffered droughts in some seasons in 2005, and so did some northeastern states and Minas Gerais, whose droughts occurred in the summer of 2006.

When it comes to observed temperature data for the period, only in the fall of 2005 were temperatures lower than the average in Brazil. The year 2005 was, in general, warmer than normal in all seasons.

4.4 Results

Since the dependent variable, TE, is a continuous variable limited to the range [0,1], Ordinary Least Square (OLS) regression might not be appropriate, as it can predict values outside this range. Besides its simplicity and linearity assumption, linear regression can also be justified when the values of the dependent variable fall mostly between 0.2 and 0.8.

Thus, besides the OLS regression, a Generalized Linear Model (GLM) approach with a logit link function⁹⁴ is compared to the OLS results. Censored regression can also be estimated, such as a two-limit Tobit model (LONG, 1997), to control for the interval range of the dependent variable. The two latter options deal with the limited variable problem of the dependent variable.

Therefore, equation 4.8 is estimated using the following estimation methods: OLS; GLM; Tobit, with the standard errors generated by bootstrap with 1000 replications.

The complete results are described in Table 4.5 and indicate no significant difference among the models, suggesting that the OLS approach is best suited for the analysis due to its simplicity and linearity.

Table 4.5: Estimation results for TE.

Variables	OLS	TOBIT	GLM [#]
% of farmers in cooperatives or associations	0.0790***	0.0790***	0.0802***
% of farmers that own the land	-0.00544	-0.00544	-0.00545
% of tenant farmers	0.162***	0.162***	0.165***
% of farms that use pest control	0.0116	0.0116	0.0117
% of population with 0 to 4 years of schooling	-0.00773***	-0.00773***	-0.00783***

⁹⁴ The GLM model is a relaxation of the previous model, allowing the linear model to be related to the response variable by a link function and the magnitude of the estimated variance to be a function of the predicted values (NELDER; WEDDERBURN, 1972).

Variables	OLS	TOBIT	GLM [#]
% of population with 5 to 8 years of schooling	-0.00632***	-0.00632***	-0.00640***
% of population with 9 to 11 years of schooling	-0.0111***	-0.0111***	-0.0113***
% of population with undetermined schooling	0.000658	0.000658	0.000714
% of farmers that used some type of credit	0.0588**	0.0588**	0.0596**
Altitude of the municipality	3.2e-06	3.2e-06	3.3e-06
Average size of farms (in hectares)	-0.00050***	-0.00050***	-0.00051***
Squared average size of farms (in hectares)	3.98e-07***	3.98e-07***	4.11e-07***
Agricultural HHI	0.222***	0.222***	0.226***
% of female farmers	3.58e-05	3.58e-05	4.10e-05
% of farmers with 1 to 5 years of experience	-0.000463	-0.000463	-0.000465
% of farmers with 5 to 10 years of experience	0.000407	0.000407	0.000417
% of farmers with more than 10 years of experience	7.11e-05	7.11e-05	7.41e-05
% of family farms	0.00102***	0.00102***	0.00103***
Index for logistic cost to São Paulo	-0.0582	-0.0582	-0.0589
Degraded agricultural area (in hectares)	-0.223	-0.223	-0.229
[Rainfall - E(Rainfall)]/σ in the summer of 2006	0.0181*	0.0181*	0.0184*
[Rainfall - E(Rainfall)]/σ in the summer of 2005	0.0340***	0.0340***	0.0346***
[Rainfall - E(Rainfall)]/σ in the fall of 2006	-0.0341***	-0.0341***	-0.0345***
[Rainfall - E(Rainfall)]/σ in the fall of 2005	-0.0120	-0.0120	-0.0122*
[Rainfall - E(Rainfall)]/σ in the winter of 2006	0.0654***	0.0654***	0.0663***
[Rainfall - E(Rainfall)]/σ in the winter of 2005	-0.00472	-0.00472	-0.00486
[Rainfall - E(Rainfall)]/σ in the spring of 2006	-0.0108	-0.0108	-0.0110
[Rainfall - E(Rainfall)]/σ in the spring of 2005	0.00176	0.00176	0.00172
[Temp. - E(Temp.)]/σ in the summer of 2006	-0.000871	-0.000871	-0.000776
[Temp. - E(Temp.)]/σ in the summer of 2005	0.00325	0.00325	0.00330
[Temp. - E(Temp.)]/σ in the fall of 2006	-0.0218	-0.0218	-0.0221
[Temp. - E(Temp.)]/σ in the fall of 2005	-0.0208	-0.0208	-0.0210
[Temp. - E(Temp.)]/σ in the winter of 2006	0.0310**	0.0310**	0.0315**
[Temp. - E(Temp.)]/σ in the winter of 2005	-0.0448***	-0.0448***	-0.0455***
[Temp. - E(Temp.)]/σ in the spring of 2006	-0.0168	-0.0168	-0.0172
[Temp. - E(Temp.)]/σ in the spring of 2005	0.0499***	0.0499***	0.0506***
Sigma (Tobit model)		0.147***	
Constant	1.119***	1.119***	
Test for climate variables^{##}: Chi-square₍₁₆₎	109.78***	112.84***	112.47***
Observations	4,473	4,473	4,473
AIC	-4,376	-4,374	0.95
BIC	-4,139	-4,131	-36,875
log-likelihood		2,225	-2,094

*** p<0.01, ** p<0.05, * p<0.1; [#] marginal effects calculated at the sample mean.

^{##} Joint test for the H₀ that all climate variables' coefficients are zero.

The results indicate that to be a cooperative member seems to generate technical gains for farmers: if the proportion of farmers' membership increases by 12 percentage points, TE goes up by approximately 0.01. Moreover, the estimated coefficients also suggest that tenant farmers seem to be more efficient than owners. Municipalities with 6 p.p. more tenant farmers have 0.01 higher efficiency. This result is in line with the work of Helfand and Levine (2004) for the Brazilian Midwest and also agrees with the argument of Solis *et al.* (2009), according to which producers that do not own the land might have more need of revenue and, thus, put more effort into their farming.

The omitted group to estimate the regression in the dummy for education is percentage of population with more than 12 years of schooling (higher educated population). The results indicate that higher education contributes positively to agricultural TE, as does finished elementary school, in comparison with other schooling levels.

There is no statistically significant difference between the genders, meaning that women and men are equally effective in running farms. When it comes to experience of farmers (the omitted group in the group dummy is less than a year of experience), the result indicates no statistically significant differences due to experience on efficiency.

Access to credit also seems to be an important variable to increase farmers' efficiency, in accordance with the finding of Taylor and Shonkwiler (1986). Approximately 17 p.p. more farmers using credit increase the efficiency by 0.01. Another variable with statistically significant contribution to TE is specialization of production. The HHI effect indicates that as specialization increases (approaches one), the efficiency of farmers also increases.

When it comes to the farm size effect on efficiency, the result seems to agree with those reported in the literature with respect to nonlinearity and inverse size of the effect (HELFAND; LEVINE, 2004). The effect is negative until 620 hectares, when the sign changes to positive (most farms greater than 620 hectares are in the Midwest). Family farms seem to be slightly more efficient than other farms. Despite its significance, the size of the effect is very small.

The joint test for the significance of climate anomalies shows that these variables are relevant to explain the differences in efficiency among the municipalities. Defining droughts as a climate anomaly in which observed rainfall is two standard deviations below normal ($\alpha = 2$), the result indicates that droughts would have reduced farmer

efficiency during the summer of 2005 (decreasing farmers' efficiency by 0.068) and 2006 (decreasing efficiency by 0.036) and in the winter of 2006 (decreasing efficiency by 0.13). The magnitude of these results is quite large compared to the previous effects discussed.

The only season that shows a positive effect of droughts (or negative effect of floods) is the fall of 2006, which is normally a harvest season for soybeans and maize. In harvest periods, floods are generally harmful, which is confirmed by the estimated results. However, fall is the growing season for winter crops (normally crops adapted to more temperate climate, such as wheat and triticale, among others). The net result from both of these forces is positive.

When it comes to cold stress effects on agriculture, colder temperatures in the winter of 2006 and spring of 2005 were harmful to producers, decreasing efficiency by approximately 0.062 and 0.1, respectively.

By using the estimated coefficients, the total profit loss or gain due to weather conditions in 2006 can be calculated by comparing the efficiency level when no anomalies occurred in rainfall or temperature in 2005 and 2006 ($C = 0$) with the efficiency level considering the occurrence of the anomalies (C is as observed). Thus, the difference in efficiency (ΔTE) can be converted into profit difference for each municipality in the sample.

The impact of the 2005 and 2006 anomalies on TE (ΔTE) is calculated and transformed into variation in profits ($\Delta \Pi$), according to the following equation:

$$\Delta TE = \frac{\Delta \Pi(.)}{\Pi^*(.)}$$

$$\Delta \Pi(.) = \Delta TE \cdot \Pi^*(.) = \Delta TE \frac{\Pi(.)}{TE} \quad (4.9)$$

The change in profits is estimated by municipality, as well as the standard error of the estimates. Considering only the statistically significant effects by municipality, the average effect is a loss of profits due to rainfall anomaly at the end of 2005 and 2006. The total loss from lack of rainfall is estimated at 5.6% of the current farmers' profits, in general. This result reflects the drier summer season observed both in 2005 (overall Brazil) and 2006 (northeastern and southern regions and Minas Gerais).

When it comes to the estimated temperature effects on profits, there is a gain in profits due to the year-end 2005 and year-end 2006 temperature conditions (detailed in Section 4.3.2) of 3.34% (Table 4.6). As colder temperatures cause more harmful effects on crops than warmer temperatures, the above-average temperatures in 2005 and 2006 had a positive impact on farm efficiency.

Following the same procedure, droughts and cold stresses are simulated in the country, in order to give the sensitivity of the losses. Assuming a 2 standard deviation reduction in rainfall (droughts) and in temperatures (cold stresses) in Brazilian municipalities, the lost profit by municipality can be calculated. Considering only the statistically significant impacts, the total losses from these events are 13.2% and 30.5%, for cold stresses and droughts respectively.⁹⁵ The estimates suggest that droughts are the most harmful climate anomaly in Brazilian agriculture. These effects are summarized below, as well as the calculation in terms of monetary losses.

Table 4.6: Estimated impact of weather anomalies on profits, Brazil.

Estimates	% of profits	Loss (-) or gain (+) in million reais (Dec-2006)	Loss (-) or gain (+) in million dollars (Dec-2011)⁹⁶
<i>2005 and 2006 anomalies</i>			
Rainfall	-5.60%	-21,440.7	-14,879.6
Temperature	3.34%	12,803.2	8,885.3
<i>Drought or cold stress</i>			
Drought	-30.50%	-116,689.1	-80,981.0
Cold stress	-13.19%	-50,474.2	-35,028.5

The average loss of profits that farmers face under the occurrence of extreme weather events is a proxy for farmers' maximum willingness to pay to protect themselves financially against drastic unforeseen weather changes. Thus, in 2006 the willingness to pay for the lack of rainfall in the country was about 15 billion dollars, a considerable amount in terms of agricultural outcomes. The net effect, including the profit gain with increased temperature, is negative in 5 billion dollars (in 2011 values). This result is very similar to the direct damage of climate anomalies on agriculture in 2005 calculated by Porsse *et al.* (2012).

⁹⁵ Droughts are assumed to be two-standard deviation negative anomalies in rainfall; cold stress is assumed to be two standard deviation negative anomalies in temperatures.

⁹⁶ Dollar amounts in 2011 are calculated by updating the 2006 values using the IPCA and converting it to dollars by the average exchange rate for the end of 2011. Source: Sisbacen PTAX800.

When it comes to the expected losses by region, the Midwest and South regions are slightly more affected by both harmful problems than the other regions.

Table 4.7: Percentage of profit losses due to climate anomalies, by region.

Region	Cold stress	Drought
North	-13.1%	-30.3%
Northeast	-13.0%	-30.0%
Southeast	-12.8%	-29.5%
South	-13.6%	-31.4%
Midwest	-15.5%	-35.9%

4.5 Conclusion

Extreme weather events directly impact farmers' outcomes. The basic hypothesis assumed in this chapter is that once farmers have decided which and how much crops/animal products to produce, extreme events (or climate anomalies) will divert them from optimal profit through harvest failures (cattle losses) or change in productivity.

The translog profit frontier equation of Chapter 3 is used in this chapter to estimate technical efficiency for a representative farmer of each Brazilian municipality, using data from the Agricultural Census of 2006. The TE is not rejected by the data, indicating that efficiency levels differ in a statistically significant way among Brazilian farmers.

The estimation of the TE leads to modeling possible determinants of farmers' deviation from optimum choices, which can be imposed by exogenous forces. This work proposes climate anomaly as a relevant determinant of farming efficiency.

Besides weather anomalies, the most relevant actions to increase farmers' efficiency used here as control variables are: membership in cooperatives or other associations; local higher education; credit access; and crop specialization. These factors might be relevant to increase efficiency and alleviate potential harmful effects of extreme weather events (DERCON, 1998; ELLIS, 2000). All these measures can help farmers to escape poverty by being more efficient and also by protecting their investments. In particular, to participate in agricultural cooperatives is a common mechanism of defense for small agricultural producers when it comes to adverse climate and market conditions in Brazil

(BUAINAIN *et al.*, 2007).

When it comes to the weather effects, the econometric test shows that climate anomalies are jointly relevant to explain the differences of technical efficiencies. The average effect due to lack of rainfall anomaly on farmer TE (during the summer months of 2005 and 2006) is a loss of 5.6% of the current farm profits, representing almost 15 billion dollars (in values of December 2011), which may be interpreted as the farmers' maximum willingness to pay to have been protected against the unforeseen lack of rainfall in Brazil in 2006. As for the estimated temperature effects on profits, there was a gain in profits due to the year-end 2005 and year-end 2006 temperature conditions, on the order of 3.34%, or 8.9 billion dollars.

The estimates of simulated cold stresses and droughts throughout the country indicate lost profits of 13.2% to 30.5%, respectively, being slightly more intense in the southern and Midwestern regions. These percentages represent 35 and 80 billion dollars of losses, respectively.

Besides the importance of other efficiency determinants discussed to alleviate the adverse climate conditions, insurance instruments are also important actions to protect farmers from such harmful situations. Within this context, weather index insurance is gaining importance as a possible intervention to overcome the negative impacts of climate risk on rural livelihoods and agricultural production. Weather index insurance is normally linked to rainfall anomalies (droughts, floods), extreme temperatures and precipitation (frosts, hail and rainstorms), or even to crop yield thresholds (ITURRIOZ, 2009).

The use of a weather index linked to an insurance mechanism is a market-driven solution, shifting part of the responsibility to public agencies, which can provide interventions in a more sustainable development model. Hellmuth *et al.* (2009) emphasize that public-private partnership and the development of the private sector are important for the success of this approach⁹⁷. Appendix A.4.2 discusses the characteristics and modeling of this tool. Barnett and Mahul (2007) underline the importance of understanding the mechanisms of weather impact on agricultural system

⁹⁷This section is based on the document by Hellmuth *et al.* (2009). This document presents many theoretical developments in terms of index insurance, mainly focused on underdeveloped and developing countries.

models in order to design the index.⁹⁸ Thus, the approach used in this thesis might be very useful to identify these relationships.

Within this context, the point of view of Ninaut and Matos (2008) is quite relevant in terms of the implementation of insurance methods in the Brazilian market. They state that the improvement of rural insurance in Brazil is impeded by the lack of statistical information on various Brazilian regions for adequate contract pricing, which compromises the success of Brazilian programs.

The authors believe that the primary need is to consolidate rural insurance for farmers and cooperatives in Brazil and, therefore, investments are needed to set up centers for collecting meteorological data, their management and improved stratification of information on crop yields. This strategy might be a relevant way to attract insurers in several Brazilian states, due to the possibility of spatial mapping of risks and the possibility of their reduction.

⁹⁸According to Baethgen *et al.* (2008), agricultural systems have an important role for modeling a weather index in three main areas: “*Designing indices that manage basis risk in its various forms; identifying and quantifying the right risk, and understanding and evaluating potential incentives, management responses, and benefits associated with index insurance and its interaction with advance information.*”

5. CONCLUDING REMARKS

This final chapter summarizes what was learned from this thesis and how it can be applied in term of public policies, and also discusses the remaining uncertainties in the problems presented, which might be interpreted as opportunities to future research.

5.1 Summary of the objectives

Due to the concern about climate impacts on economic activities and human well-being, this study aims to contribute to the measurement of these impacts, both in the long and short term, on agricultural markets and health.

When it comes to the effect on agricultural markets, the main hypotheses first assumed, and then tested, are: the climate itself is a direct input for crop and animal production, impacting land use configuration (long-term effect); and climate is an important determinant of failures and productivity changes for almost all agricultural products through extreme weather events (short-term effect). Agricultural markets are investigated by a profit frontier approach with a translog specification.

In relation to the climate influence on human health, here dengue fever was investigated as the most relevant infectious disease in Brazil, it is assumed, and then tested, that climate conditions affect the transmission of dengue fever in the country and, consequently, the geographical distribution of the disease (long-term effect), as well as the occurrence of regional epidemics (short-term effect). Dengue incidence is modeled by a risk function of the disease controlling for potential endogeneity.

By testing and understanding the mentioned effects, this thesis intends to link two relevant agendas: finding ways to manage the climate related risks of today and improving the understanding of the future risks. The next section summarizes the main findings of the study.

5.2 Main findings

Chapter 2: Dengue study

The statistical relevance of the average climate effect on dengue incidence allowed the projection of climate change impacts on this problem in Brazil. The simulations

suggested that, as the long-term temperatures increase, the southern and central-southern states will become much more vulnerable to dengue. On the other hand, the increase in temperatures in the north and northeast regions might reduce the dengue risk due to the less favorable weather for mosquitoes.

Concerning the short-term marginal effects of climate on the dengue risk, the most relevant impact is rainfall deviation from long-term average, indicating that deviations from normal rainfall conditions in summer increase the risk of dengue when compared to normal rainfall conditions. In this way, the climate predictions, as the ones calculated by INPE and INMET, can be very useful to help preventing dengue epidemics in summer and fall seasons.

Chapter 3: Agricultural study for climate change

The results of Chapter 3 indicated that, if the climate change forecast are confirmed, almost all the agricultural products in Brazil will be negatively affected, especially cattle raising, coffee and maize production. Soybean production is positively affected by the expected temperature changes (in line with IPCC, 2007), except for the Midwest region, where negative impacts are also estimated.

In monetary values of 2011, the total loss varies from 20.2 to 22.2 billion dollars (2040-2069, scenarios B2 and A2 respectively) and 29.5 to 40 billion dollars (2070-2099, B2 and A2 respectively) for the negatively affected products. The balance of gains and losses indicates net losses of 9.8 to 12% for 2040-2069 and 8.7 to 21% for 2070-2099 in terms of the agricultural GDP in 2011.⁹⁹

The results from this chapter also distinguish the Midwest, Northeast (except for scenario A2 for 2070-2099), and Southeast regions as the most vulnerable agricultural areas if future changes in temperature occur as expected. The South and North regions can expect positive effects from possible climate changes. These results are in accordance with the literature.

Chapter 4: Agricultural study for extreme weather

The evidence gathered by this chapter corroborates that, in general, droughts and cold stresses cause harmful effects to agriculture in Brazil. In 2006, the estimated loss from

⁹⁹ According to IBGE, the 2011 agricultural GDP for Brazil is R\$ 192.7 billion, or US\$ 102.7 billion.

rainfall anomalies was approximately 15 billion dollars (in 2011 values). The southern and Midwestern regions are slightly more vulnerable than the other regions.

Simulations are performed in order to calculate the dimension of losses due to extreme weather events: assuming droughts and cold stresses in Brazil as a whole, the total lost profit is about 81 and 35 billion dollars, respectively.

5.3 Policy discussion

Expected climate change

Due to the longer-term expectations over climate evolution and its impact on agriculture and dengue incidence, it is important to emphasize the relevance of governments in this context. Policymakers are the only agents that think about the sustainability of the country in the long run in order to plan specific actions. In this sense, once we are aware of the expected climate change impacts on agriculture, adaptation measures are long-term measures which need urgent actions to allow the necessary lead time to build flexible production systems.

In this study, the adaptation measures needed to offset the expected effect of climate change on agricultural production are related to the technological variables included in the model. As natural resources are limited, technology seems to be the solution to the problem. Planned adaptation actions to prepare for climate change should build on and coordinate with local adaptation, while pursuing sector-level and long-term adjustment (FAO, 2011c).

According to the estimates, use of irrigation is the main compensation instrument to reduce the expected climate change impacts. However, technological instruments such as transgenic/certified seeds, confined cattle and tilled area are also important adaptation measures to smooth the climate change effects. In particular, the use of transgenic/certified seeds is an example of sustainable use of genetic resources in agricultural products which are essential to achieve food security. This study suggests that the development and use of genetics will also serve as an insurance policy in response to potential changes in production conditions and must be taken into account when addressing adaptation measures.

Short-term interventions

Another important aspect is that monetary and social losses, due to climate change and variability in agriculture, affect more adversely small and poorer farmers. Due to this equitable problem, public intervention is needed to stimulate the market to produce alternatives.

Some relevant evidence found may help farmers to become more efficient, such as membership in cooperatives, crop specialization, better credit access, and higher level education. However, when it comes to climate shocks, these can be mainly mitigated by the intense use of an insurance instrument based on the occurrence of weather shocks. The estimated dimension of a rural insurance market for extreme weather is big, considering the maximum farmer propensity to pay for such instrument in 2006, approximately 15 billion dollars due to the lack of rainfall, in 2011 values.

This study suggests weather index insurance, which has increased importance in the recent literature, to model the average insurance need which is based on the occurrence of weather shocks in the Brazilian agriculture. However, as Maia *et al.* (2010) pointed out, there are many difficulties from the autonomous development of a rural insurance market besides the lack of information and spatial positive correlation of damages¹⁰⁰ intrinsic to this market.¹⁰¹ The participation of farmers in the agricultural insurance market in Brazil is still very low (MAIA *et al.*, 2010).¹⁰²

Chapter 2 also presents important evidence to base government interventions for dengue control. The results for expenditures for epidemiological surveillance are indication of ineffectiveness of such expenditures due to the delay in incurring them. The current local system of monitoring dengue in Brazil is based on the observation of dengue cases in January and February, with occasional interventions by spraying insecticides to kill

¹⁰⁰ The insurance market might be imperfect due to the positive spatial correlation of losses (limiting the risk reduction capacity), increasing farmer risks (BAETHGEN *et al.*, 2008).

¹⁰¹ As Appendix A.4.2 suggests, the usual problems of asymmetric information and moral hazard are reduced from the weather index insurance approach.

¹⁰² The Brazilian government started a program to encourage agricultural insurance (Programa de Subvenção ao Prêmio do Seguro Rural) at the end of 2005, which is increasing the coverage of insurance in the country. When it comes to the private market, the main insurance companies for agriculture and livestock are Porto Seguro, Aliança do Brasil, AFG, Mapfre, Nobre Seguros and Seguradora Brasileira Rural. The insurance companies cover up to 70% of the average volume of production. However, the adherence to this insurance model is small. According to the National General Insurance Association (*Federação Nacional de Seguros Gerais*), private contracts cover 8% of the country's planted area. Many producers argue that the insurance costs do not compensate the safety they provide. The productivity calculations, which could diminish the cost for producers, are based on the average production, which is underestimated for some farmers.

mosquitoes and their larvae where an increase in the number of cases is detected. This procedure, besides being more expensive, is not effective in reducing dengue locally.

Those expenditures are also made at the municipal sites, not controlling infected mosquitoes that cross municipal borders. The evidence of spatial contagion from neighboring municipalities suggests that integrated actions are needed to control the dengue fever spread during epidemics. Most of the literature indicates the importance of developing or improving current surveillance systems to control diseases.¹⁰³ Therefore, it represents the basis of knowledge upon which public health response, programs, and policy depend. Quality surveillance ensures appropriate and targeted interventions. According to Nsubuga *et al.* (2006), the use of climate data in surveillance is still underdeveloped, but has the potential to enhance the usefulness of this tool by adding predictive and explanatory power. This study is an attempt to discuss a mechanism based on climate data to better control dengue in the country.

5.4 Summary of the contributions

Dengue in Brazil

1. Use of climate data from Brazilian weather stations.
2. Testing both the average climate conditions and short-term climate shocks impacts on dengue;
3. Considering non-linearities in the climate-dengue relationship detected by the epidemiology literature;
4. Estimation of important determinants of the risk of dengue, such as local epidemiological expenses, as well as other social vulnerabilities;
5. Testing the time dependence and spatial contagious in dengue incidence;
6. Projecting the expected effect of climate change on dengue fever spatial distribution;
7. Calculation of a vulnerability index based on socio-economic conditions and average climate in Brazil; and

¹⁰³ According to the WHO (2012), public health surveillance is the “continuous, systematic collection, analysis and interpretation of health-related data needed for the planning, implementation, and evaluation of public health practice. Such surveillance can: i) serve as an early warning system for impending public health emergencies; ii) document the impact of an intervention, or track progress towards specified goals; and iii) monitor and clarify the epidemiology of health problems, to allow priorities to be set and to inform public health policy and strategies”.

8. Discussion of a mechanism of risk assessment for prevention of dengue epidemics based on short-term climate predictions.

Agriculture in Brazil

1. Insertion of the majority of agricultural products by volume in the analysis;
2. Consideration of many technological variables as quasi-fixed inputs inside a profit function approach;
3. Calculation of different compensation measures for the potential harmful climate change;
4. Use of climate data from Brazilian weather stations.
5. Inclusion of an efficiency analysis for agriculture by using profit frontier approach;
6. Linking short-term climate variations inside the technical efficiency of farmers;
7. Measurement of extreme weather events' impact on agricultural outcomes;
8. Discussion of a weather index insurance procedure to avoid extreme weather losses.

5.5 Limitations and future research

Future research regarding the dengue fever analysis could increase the time horizon by using annual datasets such as the *Pesquisa Nacional por Amostra de Domicílios* (PNAD). However, the impossibility to identify municipalities in this dataset might be an obstacle for matching socio-demographic information with climate data. Studies *in loco* are also a good opportunity to understand dengue fever contagion by geocoding the cases and observing the local social conditions, which could better identify the inequality in sanitation infrastructure provision inside the municipality. The dengue vulnerability index is also a tool that can be better investigated, as it gathers much information about the current susceptibility of dengue in the country.

When it comes to the limitations and possibilities of future research in the agricultural studies, all the climate change compensation actions are measured in terms of the variation of the adaptation technique usage. However, there are many costs and barriers that were not taken into account in this study, such as investment and opportunity cost comparisons, which are helpful to compare those techniques best through cost-benefit analysis. A future work could map the investment need of each technique, as well as the penetration of them in Brazilian municipalities, in order to improve the policy

discussion. With these concerns in mind, the Agricultural Census, the source of the data used in this analysis, could include new questions regarding the investment need of those technologies, which seem to be relevant for farmers' alleviation of future climate risks.

Another limitation of this thesis is that it uses partial analysis of the climate-sensitive problems discussed. This is even more relevant in the agricultural analysis, where prices are considered fixed in the long term in order to perform the simulations. Simulations of changes in prices can be done in general equilibrium approaches.

The extreme weather analysis can be improved by developing a frost index or hail index to include in the TE equation, instead of the cold stress index. Although the occurrence of frosts is related to colder weather, frosts also need specific conditions of altitude and humidity to occur.

When it comes to the risk assessment in agriculture, one problem faced by the implementation of these procedures, such as weather index insurance, is the lack of precision and frequency of climate information for Brazil. The lack of statistical information on various Brazilian regions hinders adequate contract pricing.

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Figure A.2.1: Average seasonal rainfall, in mm per month, 1980 to 2009

Source: Data from INMET. Prepared by the author.

Figure A.2.2: Average seasonal air temperature, in °C per month, 1980 to 2009

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Figure A.2.4: Percentage of municipalities with at least one case of dengue during 2010.

Source: Data from SINAN (Health Ministry). Prepared by the author.

APPENDIX A.2.2: DESCRIPTIVE STATISTICS OF CHAPTER 2

The following table presents the basic statistics for the variables tested in the model.

The comments on the variables' information can be read in Section 2.3.

Table A.2.1: Basic statistics, all variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>Educational Variables (years of schooling dummies)</i>					
No schooling or element. school incomplete	5565	63.26	9.86	26.00	90.6
Compl. element. and incomplete high school	5565	15.67	3.12	4.33	35.1
Compl. high school and incompl. college	5565	16.47	5.62	1.52	40.9
Complete college	5565	4.17	2.61	0.18	26.7
<i>Educational Variables (illiteracy rate by gender)</i>					
Illiteracy rate	5565	14.74	8.94	0.90	41.6
Illiteracy rate - men	5565	15.59	10.41	0.80	48.2
Illiteracy rate - women	5565	13.88	7.66	0.80	40.4
<i>Income Variables (income levels – multiples of minimum monthly wage)</i>					
% inc from 0 to 0.25 x min. wage	5565	5.74	4.45	0.17	24.5
% inc from 0.25 to 0.5 x min. wage	5565	5.14	2.78	0.37	17.5
% inc from 0.5 to 1 x min. wage	5565	25.90	5.65	7.79	44.7
% inc from 1 to 2 x min. wage	5565	15.88	8.57	2.94	47.9
% inc from 2 to 3 x min. wage	5565	4.34	3.07	0.34	18.6
% inc from 3 to 5 x min. wage	5565	3.01	2.15	0.16	13.3
% inc from 5 to 10 x min. wage	5565	1.60	1.29	0.00	11.9
% inc from 10 to 15 x min. wage	5565	0.21	0.23	0.00	3.3
% inc from 15 to 20 x min. wage	5565	0.15	0.19	0.00	2.8
% inc from 20 to 30 x min. wage	5565	0.07	0.10	0.00	2.5
% inc more than 30 x min. wage	5565	0.05	0.07	0.00	1.5
% inc with no income	5565	37.90	8.57	9.75	74.2
Gini Coefficient (labor income)	5565	0.46	0.07	0.23	0.78
<i>Income Variables (median income by urban/rural)+A60</i>					
Median income	5565	958.51	398.38	134.00	3000.0
Median income (urban households)	5565	1043.25	386.77	250.00	3000.0
Median income (rural households)	5497	812.88	361.01	0.00	2700.0
<i>Possession of Durable Goods</i>					
Radio	5565	77.84	13.19	13.28	100.0
TV	5565	90.81	8.23	19.91	100.0
Computer	5565	21.33	13.98	0.44	72.7
Computer + Internet	5547	15.03	11.35	0.10	68.6
Motorcycle	5565	26.15	11.39	1.45	71.6
Automobile	5561	31.89	19.94	0.14	90.7

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>Waste Disposal</i>					
Collected or burned	5564	70.26	21.84	0.00	100.0
Precarious (discarded)	5564	4.83	6.33	0.00	58.6
None	5565	1.63	3.67	0.00	43.2
No indoor bathroom in the household	5359	6.39	10.04	0.01	67.2
<i>Sewage System</i>					
Integrated network	5565	29.45	31.52	0.00	99.9
Septic tanks	5565	12.83	16.42	0.00	97.3
Integrated network or tanks	5565	42.30	31.28	0.00	100.0
Rudimentary cesspits	5565	43.76	29.03	0.00	99.1
Drainage ditch	5565	3.06	4.50	0.00	50.7
Discharged into rivers, lakes, sea	5565	2.51	6.55	0.00	79.1
Other	5565	2.24	4.25	0.00	69.2
None	5565	6.15	9.93	0.00	67.2
<i>Water Supply</i>					
Water access	5565	89.54	15.08	5.16	100.0
Sanitation system	5557	65.74	20.90	0.09	100.0
Other supplies (artesian well, etc.)	5552	19.08	15.65	0.11	93.9
No piped water	5106	11.40	15.40	0.01	94.8
<i>Climate Variables by season in 2010</i>					
Avg. temperature (C) summer	5555	25.24	1.66	19.47	28.5
Avg. temperature (C) fall	5555	23.35	3.23	14.38	29.5
Avg. temperature (C) winter	5555	20.73	4.40	10.69	30.5
Avg. temperature (C) spring	5555	23.54	3.53	14.49	31.2
Relative humidity (%) summer	5555	75.76	4.50	60.92	90.4
Relative humidity (%) fall	5555	76.50	3.42	66.71	85.1
Relative humidity (%) winter	5555	68.92	9.18	48.22	83.8
Relative humidity (%) spring	5555	67.56	6.12	49.54	79.9
Rainfall (mm) summer	5555	159.90	68.76	24.99	396.6
Rainfall (mm) fall	5555	122.88	46.15	49.29	346.0
Rainfall (mm) winter	5555	51.87	48.45	2.28	258.7
Rainfall (mm) spring	5555	92.27	41.02	15.02	175.0
<i>Climate Variables by season, average from 1980 to 2009 (long term - lt)</i>					
Avg. temperature (C) summer	5564	24.56	1.63	18.85	27.9
Avg. temperature (C) fall	5564	23.03	2.54	15.91	28.5
Avg. temperature (C) winter	5564	20.50	4.02	12.30	29.8
Avg. temperature (C) spring	5564	23.39	3.09	15.24	30.1
Relative humidity (%) summer	5564	76.29	4.40	61.73	90.5
Relative humidity (%) fall	5564	77.92	3.34	67.30	89.1
Relative humidity (%) winter	5564	71.63	6.08	53.19	84.3

Variable	Obs	Mean	Std. Dev.	Min	Max
Relative humidity (%) spring	5564	69.64	5.63	52.31	82.9
Rainfall (mm) summer	5555	171.52	57.19	46.83	303.2
Rainfall (mm) fall	5555	132.38	50.06	57.70	383.4
Rainfall (mm) winter	5555	60.06	43.75	4.72	294.0
Rainfall (mm) spring	5555	95.74	45.63	4.50	180.2

Climate Deviations in 2010 from long term average by season (short term - st)

Avg. temperature (C) summer	5555	0.67	0.41	-1.23	4.0
Avg. temperature (C) fall	5555	0.32	0.82	-3.29	2.4
Avg. temperature (C) winter	5555	0.24	0.70	-2.83	3.1
Avg. temperature (C) spring	5555	0.15	0.59	-2.10	2.1
Relative humidity (%) summer	5555	-0.53	2.74	-9.08	5.3
Relative humidity (%) fall	5555	-1.42	2.36	-9.94	5.1
Relative humidity (%) winter	5555	-2.71	4.11	-18.69	9.4
Relative humidity (%) spring	5555	-2.08	2.72	-16.14	6.0
				-	
Rainfall (mm) summer	5555	-11.62	33.29	115.33	136.5
				-	
Rainfall (mm) fall	5555	-9.49	47.08	133.18	189.7
				-	
Rainfall (mm) winter	5555	-8.19	22.22	103.42	101.0
Rainfall (mm) spring	5555	-3.48	22.53	-75.25	63.9

Population Structure and Age Distribution

Total population	5555	34318.65	203292.60	805.00	#####
Percentage of urban households	5555	0.64	0.22	0.04	1.0
Percentage of women	5565	49.50	1.57	18.91	54.2
% of people from 0 to 9 years old	5565	15.74	3.48	4.73	36.9
% of people from 10 to 19 years old	5565	18.92	2.65	5.86	27.4
% of people from 20 to 29 years old	5565	16.62	2.02	7.24	38.0
% of people from 30 to 49 years old	5565	27.00	2.84	15.79	38.9
% of people from 50 to 69 years old	5565	16.17	3.65	4.64	31.8
% of people 70 or more years old	5565	5.55	1.73	0.68	14.5

Dengue Notifications by Year

Dengue cases – 2002	5564	126.13	2149.05	0.00	147272.0
Dengue cases – 2003	5564	50.13	357.41	0.00	12408.0
Dengue cases – 2004	5564	12.99	110.02	0.00	3753.0
Dengue cases – 2005	5564	27.13	244.83	0.00	11815.0
Dengue cases – 2006	5564	47.87	446.07	0.00	15617.0
Dengue cases – 2007	5564	89.90	818.18	0.00	44550.0
Dengue cases – 2008	5561	99.97	1642.27	0.00	110093.0
Dengue cases – 2009	5561	70.28	622.13	0.00	25553.0
Dengue cases – 2010	5561	176.42	1399.50	0.00	52773.0
Dengue cases – 2011	5561	131.59	1529.34	0.00	80536.0

Variable	Obs	Mean	Std. Dev.	Min	Max
<i>Health Information/Expenditures</i>					
Number of private hospitals	5563	0.01	0.07	0.00	1.5
Number of public hospitals	5563	0.91	2.29	0.00	103.0
Number of visits (FHP)*	5562	16408.77	118793.70	0.00	8100000.0
Number of families covered by the FHP	5562	1692.96	11575.63	0.00	740181.0
% of families covered by the FHP/total	5562	0.18	0.27	0.00	1.0
Number of visits per family (FHP)	5562	8.15	113.95	0.00	6321.0
Health expenditures per inhabit. (2005)	5565	194.96	118.49	0.00	1767.5
FHP expenditures per inhabit. (2005)	5565	115.14	113.42	0.00	1320.7
Epidemiological expenditures per inhabit. (2005)	5565	2.18	5.07	0.00	113.1
Health expenditures per inhabit. (2006)	5565	238.68	130.48	0.00	1804.6
FHP expenditures per inhabit. (2006)	5565	145.81	129.01	0.00	922.7
Epidemiological expenditures per inhabit. (2006)	5565	2.88	7.17	0.00	240.5
Health expenditures per inhabit. (2007)	5565	258.32	141.14	0.00	2037.9
FHP expenditures per inhabit. (2007)	5565	159.65	139.46	0.00	1265.8
Epidemiological expenditures per inhabit. (2007)	5565	3.10	7.45	0.00	342.3
Health expenditures per inhabit. (2008)	5565	294.40	174.52	0.00	2310.7
FHP expenditures per inhabit. (2008)	5565	183.61	167.57	0.00	1276.3
Epidemiological expenditures per inhabit. (2008)	5565	3.63	9.56	0.00	254.8
Health expenditures per inhabit. (2009)	5565	352.75	675.25	0.00	34204.0
FHP expenditures per inhabit. (2009)	5565	204.81	169.69	0.00	1308.0
Epidemiological expenditures per inhabit. (2009)	5557	3.98	7.25	0.00	178.1
Health expenditures per inhabit. (2010)	5557	368.83	198.56	0.00	1928.2
FHP expenditures per inhabit. (2010)	5557	227.07	192.54	0.00	1601.7
Epidemiological expenditures per inhabit. (2010)	5557	4.72	8.36	0.00	180.0
* Family Health Program					
<i>Location Variables</i>					
Dummy for border municipalities	5564	0.11	0.31	0.00	1.0
Dummy for coastal municipalities	5564	0.07	0.26	0.00	1.0
Transportation costs - average	5564	464.63	409.42	0.00	5949.0
Distance to the state capital (in km)	5507	253.20	163.68	0.00	1476.3
Municipal area in square km	5565	1527.89	5622.29	3.60	159533.4
Population density (habit. per km ²)	5565	108.20	572.44	0.13	13024.6
% of people working out of municip.	5562	11.99	10.17	0.12	69.8
NDVI (2006)	5561	0.58	0.10	0.06	0.8

APPENDIX A.2.3: WEATHER ANOMALIES IN 2010

The following maps show the 2010 deviations in weather during the summer season.

Figure A.2.5: Weather anomalies in 2010, observed weather deviation from the long-term (LT) average (1980-2009).

APPENDIX A.2.4: BRAZILIAN BIOMES

The Brazilian biomes considered in the analysis are shown in the following figure:

Figure A.2.6: Spatial Distribution of Brazilian Biomes

APPENDIX A.2.5: AVERAGE MARGINAL EFFECTS, DENGUE RISK MODEL

The average marginal effects for the Poisson model, in terms of dengue level, are presented in the figures below:

Figure A.2.7: Average marginal effects for normal monthly temperature (summer, 1980-2009, in °C and number of dengue cases)

Figure A.2.8: Average marginal effects for normal relative humidity, RH (summer, 1980-2009, in % and number of dengue cases)

Figure A.2.9: Average marginal effects for normal rainfall (summer, 1980-2009, in mm and number of dengue cases)

Figure A.2.10: Average marginal effects for 2010 temperature deviation (summer, in °C deviation from long-term average per month)

Figure A.2.11: Average marginal effects for 2010 relative humidity deviation (summer, in % deviation from long-term average per month)

Figure A.2.12: Average marginal effects for 2010 rainfall deviation (summer, in mm deviation from long-term average per month)

APPENDIX A.3.1: DERIVATION OF THE ELASTICITIES FROM THE PROFIT FUNCTION VARIABLES

Price elasticities

The classic own price elasticities (ε) for product j are measured from the quantity's (q) percentage change due to a percentage variation in its prices (p):

$$\varepsilon_{jj} = \frac{\partial q_j / q_j}{\partial p_j / p_j} \equiv \frac{\partial \ln(q_j)}{\partial \ln(p_j)} \quad (\text{A.3.1})$$

In the translog case, the Hotelling Lemma generates share equations (s , calculated in terms of profits, π), instead of supply/demand equations, which increases the steps needed to calculate the price elasticities:

$$s_j = \frac{p_j q_j}{\pi} \quad (\text{A.3.2})$$

In natural logarithmic terms:

$$\ln(s_j) - \ln(p_j) + \ln(\pi) = \ln(q_j) \quad (\text{A.3.3})$$

Thus, the own price elasticity for the netput j can be described as:

$$\begin{aligned} \varepsilon_{jj} &= \frac{\partial \ln(q_j)}{\partial \ln(p_j)} = \frac{\partial \ln(s_j)}{\partial \ln(p_j)} - \frac{\partial \ln(p_j)}{\partial \ln(p_j)} + \frac{\partial \ln(\pi)}{\partial \ln(p_j)} = \frac{1}{s_j} \frac{\partial s_j}{\partial \ln(p_j)} - 1 + s_j \\ \varepsilon_{jj} &= \frac{\beta_{jj}}{s_j} - 1 + s_j \end{aligned} \quad (\text{A.3.4})$$

The formulation for the cross-price elasticities has similar derivation, generating the equations:

$$\begin{aligned} \varepsilon_{jk} &= \frac{\partial \ln(q_j)}{\partial \ln(p_k)} = \frac{\partial \ln(s_j)}{\partial \ln(p_k)} - \frac{\partial \ln(p_j)}{\partial \ln(p_k)} + \frac{\partial \ln(\pi)}{\partial \ln(p_k)} = \frac{1}{s_j} \frac{\partial s_j}{\partial \ln(p_k)} - 1 + s_k \\ \varepsilon_{jk} &= \frac{\beta_{jk}}{s_j} - 1 + s_k \end{aligned} \quad (\text{A.3.5})$$

Exogenous variables semi-elasticities

When it comes to the exogenous variables, since they are mostly measured in level form, it is possible to calculate the semi-elasticity (η_{jr}) for product j , which is measured from the quantity's (q) percentage change due to a variation on the exogenous variable (Z^r):

$$\eta_{jr} = \frac{\partial q_j / q_j}{\partial Z^r} \equiv \frac{\partial \ln(q_j)}{\partial (Z^r)} \quad (\text{A.3.6})$$

As for the price elasticity calculation, the share equations must be used to generate the effects on production. Thus, the semi-elasticity can be described as:

$$\eta_{jr} = \frac{\partial \ln(q_j)}{\partial (Z^r)} = \frac{\partial \ln(s_j)}{\partial (Z^r)} - \frac{\partial \ln(p_j)}{\partial (Z^r)} + \frac{\partial \ln(\pi)}{\partial (Z^r)} = \frac{1}{s_j} \frac{\partial s_j}{\partial Z^r} + \frac{\partial \ln(\pi)}{\partial (Z^r)}$$

$$\eta_{jr} = \frac{\gamma_{jr}}{s_j} + [\sum_{j>1}^m \gamma_{jr} \ln(p_j)] + \delta_r + \frac{1}{2} \sum_{h=1}^f \theta_{hr} Z_h \quad (\text{A.3.7})$$

Elasticities are generated by just multiplying the equation A.3.7 by Z^r .

APPENDIX A.3.2: REGULARITY CONDITIONS IN PROFIT FUNCTIONS

Many studies have emphasized that violations of the regularity conditions can affect the failure of the applicability of the duality theory to a data set (MOSCHINI, 1999; BARNETT, 2002; LUSK *et al.*, 2002), as it indicates that the second-order condition for optimizing behavior fails. For this reason, interventions such as imposition of those conditions when estimating are valid actions in applied works.

Convexity assumption in the profit function

Suppose that the farm manager is faced with uncertainty regarding the output and input prices. It is not intuitive that the manager would find it more profitable to wait until observing the prices before choosing the netput vector instead of choosing this while knowing the distribution of prices that might occur.

If α is the probability of prices p' and $(1-\alpha)$ is the probability of prices p'' , then $\Pi[\alpha p' + (1-\alpha)p''] = \alpha(p'q^*) + (1-\alpha)(p''q^*)$ is the greatest average profit that can earn when choosing the same q^* all the time. The convexity of prices can be used to prove that supply curves are upward sloping and input demand curves are downward sloping in prices. If profits are differentiable and assuming convexity:

$$\frac{\partial q_j(p)}{\partial p_j} = \frac{\partial^2 \pi^*(p)}{\partial p_j^2} \geq 0 \quad (\text{A.3.8})$$

If j is an output good, the price positively affects the supply. If j is an input good, then as p_j rises, q_j (which is a negative number) rises, i.e., the amount of the input used declines. The semidefinite positiveness of the Hessian matrix guarantees that its diagonals are all positive or zero (DIEWERT, WALES, 1987). Mundlak (2001) states that “*studies where convexity is not confirmed should go no further because the remaining results have no theoretical support.*”

According to Diewert (1974), by assuming that the variable profit function $\pi(p,z)$ is linearly homogeneous and convex in p and twice continuously differentiable with respect to the components of p at some point, (p,x) , the system of variable profit maximizing netput functions exists at this point and these netput functions are continuously differentiable, guaranteeing the next assumption.

Symmetry assumption in the profit function

If the profit function is twice differentiable, Young's Theorem on second derivatives states that (DIEWERT, 1980):

$$\frac{\partial^2 \pi(p)}{\partial p_i \partial p_j} = \frac{\partial^2 \pi(p)}{\partial p_j \partial p_i} \quad (\text{A.3.9})$$

This implies that:

$$\frac{\partial q_i(p)}{\partial p_j} = \frac{\partial q_j(p)}{\partial p_i} \quad (\text{A.3.10})$$

This expressions means that the response of the output/input to a different output/input is symmetric. Thus, the cross price derivatives are equivalent. This provides the Hotelling (1932) and Hicks (1946) symmetry restrictions on output supply and input demand functions.

Homogeneity assumption in the profit function

Homogeneity of the profit function means that $\pi(p)$ is linear homogenous in prices, which imply (Euler equation):

$$\sum_{j>1}^m \frac{\partial \ln[\pi(p)]}{\partial \ln(p_j)} + \frac{\partial \ln[\pi(p)]}{\partial \ln(p_1)} = 1 \quad (\text{A.3.11})$$

Homogeneity guarantees that individuals respond to relative prices. In the case of the translog equation, the homogeneity constraint is imposed by excluding one component and rescuing its coefficients (normalization on one price).

APPENDIX A.3.3: PRICES EXPECTED BY THE FARMERS

Three types of prices are calculated for output of the products in order to test the profit frontier model:

- i. *Estimated price*: Calculated from a Generalized Method of Moments (GMM) procedure (Arellano-Bond estimator) testing the lagged structure of price formation;
- ii. *Lagged price*: Implicit prices in the previous year are generated by dividing the total production value by the total quantity produced in that year;
- iii. *Average lagged price*: Implicit prices for the five previous years are generated by averaging the total production value by the total quantity produced during among the previous five years.

This appendix describes how the product prices are estimated (item i above), based on rational expectations model. Later in this appendix, all the prices estimates are compared. The model to estimate the price for each crop C can be described as:

$$p_{it}^C = \mu_1^C p_{i,t-1}^C + \dots + \mu_w^C p_{i,t-w}^C + trend_t \beta^C + \alpha_i + \varepsilon_{it}^C, t = w + 1, \dots, T \quad (A.3.12)$$

In which:

p_{it}^C denotes the price of crop C in municipality i in year t ¹⁰⁴;

$\mu_1, \dots, \mu_w, \beta$ are parameters to be estimated. The μ values are the weights of the lagged prices in the expectation of the future prices;

ε_{it} is the error term and α_i is a fixed effect for municipality i ;

Besides considering the state dependence (lagged variables), the dynamic model also allows the inclusion of a temporal trend in price determinants and heterogeneities (α_i). In order to correct for the endogeneity from the correlation between the lagged variables in equation A.3.12 and the error term, Arellano and Bond (1991) detailed the implementation of the instruments procedure to generate consistent estimators from the parameters of the equation. The idea behind the procedure is that it considers a list of lagged instruments to the lagged variables in the model.

¹⁰⁴ Prices must be in real terms of t .

From the weighting structure estimated above, it is possible to generate consistent predictions for the farmer's expectations for the price of crop C in year t ¹⁰⁵:

$$p_t^{e,C} = E_{t-1}(p_t^C) = \hat{\mu}_1^C p_{i,t-1}^C + \dots + \hat{\mu}_w^C p_{i,t-w}^C \quad (\text{A.3.13})$$

The idea behind this procedure is that farmers expect prices based on the information available at the time of the growing/production season (rational expectations). Following Nerlove and Fornari (1995), the use of those predicted prices inside the farmer's decision – quasi-rational expectations – generates consistent estimations when the forecast error of the equation is uncorrelated with the disturbance term of the output supply and input demand equations. The authors also affirm that there are no efficiency problems when all prices have been specified differently (and correctly) in a recursive system.

The equations are estimated by efficient GMM with the variance-covariance correction proposed by Windmeijer (2005). Autocorrelation tests are performed to verify the existence of uncorrelation among the errors and all the models reject such correlation.¹⁰⁶ These estimations are calculated by using price information from the Municipal Agricultural Survey (PAM). This survey is conducted annually by the IBGE for each municipality in Brazil and only reports physical and financial production. Table A.3.1 shows the estimations of the equation for each crop:

¹⁰⁵ The “hat” indicates the estimated parameters of the model.

¹⁰⁶ In order to perform the Sargan test, the GMM efficient model is estimated. The output of this model was omitted.

Table A.3.1: Efficient GMM estimation for the crops prices, 1999 to 2010[#].

Variables	coffee price	Milk price	Soybean price	maize price	other annual price	Other peren. price
price t - 1	0.528*** (0.0152)	0.582*** (0.0131)	0.590*** (0.0169)	0.151*** (0.0121)	0.261*** (0.0334)	-0.0694 (0.146)
price t - 2	0.0558*** (0.0114)	0.0785*** (0.0105)	-0.339*** (0.0174)	0.230*** (0.0127)	0.0329*** (0.0120)	-0.171 (0.129)
price t - 3	-0.0798*** (0.00965)	0.0548*** (0.00886)	-0.0680*** (0.0158)	0.196*** (0.0108)		-0.125 (0.161)
price t - 4	-0.0597*** (0.00964)	-0.00503 (0.00885)	0.0953*** (0.0151)	0.125*** (0.00905)		
price t - 5			0.178*** (0.0156)	0.0699*** (0.00870)		
Trend	0.0200*** (0.00278)	0.00257*** (0.000232)	-0.0118*** (0.000570)		0.00729*** (0.000945)	0.00883*** (0.00308)
Price of Maize (avg.)				-4.41e-05*** (1.31e-05)		
Constant	1.316*** (0.0618)	0.121*** (0.0104)	0.482*** (0.0201)	0.276*** (0.0545)	0.247*** (0.0216)	0.576*** (0.199)
Observations	19,582	55,484	13,051	34,804	14,380	8,820
Number of municipalities	1,992	5,193	1,250	4,776	4,940	4,678
Arellano-Bond test for zero autocorrelation in first-differenced errors	<i>not reject error uncorrelation (1%)</i>	<i>not reject error uncorrelation (1%)</i>	<i>not reject error uncorrelation (1%)</i>	<i>not reject error uncorrelation (1%)</i>	<i>not reject error uncorrelation (1%)</i>	<i>not reject error uncorrelation (1%)</i>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[#]: For other annual and perennial crops, the period analyzed was 2000 to 2006.

The following table shows the main statistics related to the measures of all expected prices developed (i), (ii), and (iii). Following this table, the map of these prices distributions is presented for coffee, which indicates that all three measures are relatively close to the spatial distribution of the actual prices. All the measures used PAM data in order to have lagged information on prices.

Table A.3.2: Summary of the price measures, real price of 2006

Variable	Total obs.	Mean	Std. Dev.	Min	Max
<i>Crop Prices (2006)</i>					
Coffee	5557	2.99	0.73	0.33	5.33
Maize	5557	0.47	0.49	0.00	5.94
Soybean	5557	0.45	0.12	0.25	0.83
Other annual crops	5557	0.32	0.27	0.02	1.50
Other perennial crops	5557	0.52	0.26	0.10	1.80
Milk	5557	0.59	0.21	0.20	1.38
<i>Crop Prices - Estimated by Arellano-Bond (2006)</i>					
Coffee	5557	3.11	0.38	1.32	4.50
Milk	5557	0.58	0.14	0.32	1.12
Soybean	5557	0.49	0.09	0.16	0.84
Other annual crops	5557	0.29	0.09	-0.08	0.42
Other perennial crops	5557	0.52	0.08	0.40	0.90
Maize	5557	0.44	0.19	0.17	2.41
<i>Crop Prices in t-1 (2005), real price for 2006</i>					
Coffee	5557	3.11	0.77	0.46	6.23
Milk	5557	0.59	0.20	0.20	1.36
Soybean	5557	0.53	0.11	0.04	1.04
Other annual crops	5557	0.33	0.29	0.02	1.49
Other perennial crops	5557	0.51	0.27	0.10	1.80
Maize	5557	0.45	0.52	0.00	5.97
<i>Crop Prices: 5-year average, real price for 2006</i>					
Coffee	5557	2.72	0.58	0.68	6.89
Milk	5557	0.58	0.20	0.22	1.28
Soybean	5557	0.62	0.06	0.38	1.13
Other annual crops	5557	0.36	0.24	0.02	1.26
Other perennial crops	5557	0.49	0.22	0.11	1.67
Maize	5557	0.50	0.26	0.16	3.14

Figure A.3.1: Comparison among prices of coffee: 2006 real prices; Estimated prices (Arellano-Bond); Prices in $t - 1$ (2005); and last five-year average, in R\$ per Kg.

APPENDIX A.3.4: EMPIRICAL STRATEGY: ESTIMATION OF THE PROFIT FRONTIER

When it comes to the profit frontier estimation, equation 3.4 shows the farmer profit frontier equation normalized for output/input 1. In order to estimate the parameters of this equation, an error component (v) is added, leading to estimation of the following equation:

$$\begin{aligned} \ln\left(\frac{\Pi_i}{p_{1,i}}\right) = & \beta_0 + \sum_{j>1} \beta_j \ln\left(\frac{p_{j,i}}{p_{1,i}}\right) + \frac{1}{2} \sum_{j>1} \sum_{k>1} \beta_{jk} \ln\left(\frac{p_{j,i}}{p_{1,i}}\right) \ln\left(\frac{p_{k,i}}{p_{1,i}}\right) \\ & + \sum_{j>1} \sum_{r=1}^f \gamma_{jr} Z_{jr,i} \ln\left(\frac{p_{j,i}}{p_{1,i}}\right) + \sum_{r=1}^f \delta_r Z_{r,i} \\ & + \frac{1}{2} \sum_{h=1}^f \sum_{r=1}^f \theta_{hr} Z_{h,i} Z_{r,i} - \tau_i + v_i \end{aligned} \quad (\text{A.3.14})$$

In which i represents the farmers, such that $i = 1, \dots, N$.

Note that τ is a positive component that shifts the profit from the optimum, given the reasons discussed in the former sections. In order to estimate this equation, Kumbhakar and Lovell (2000) suggested a maximum likelihood estimation, using the probability density function (pdf) of the composite error: $y_i = (-\tau_i + v_i)$.¹⁰⁷

Suppose that v_i is *i.i.d* and follows a normal distribution with mean zero and variance σ_v^2 and that τ_i is *i.i.d* and follows a normal distribution, positive and truncated at zero, with mean μ and variance σ_u^2 . By using the linear transformation of random variables (DEGROOT, SCHERVISH, 2002), the pdf of the composite error (y) can be written as:

$$g(y) = \int_{-\infty}^{+\infty} f_u(x_2) f_v(y + x_2) dx_2 \quad (\text{A.3.15})$$

$$g(y/\mu, \sigma_u, \sigma_v) = \int_{-\infty}^{+\infty} \left(\frac{1}{\sigma_u}\right) \frac{\phi\left(\frac{(x_2 - \mu)/\sigma_u}{[1 - \Phi\left(-\frac{\mu}{\sigma_u}\right)]}\right)}{[1 - \Phi\left(-\frac{\mu}{\sigma_u}\right)]} \phi\left(\frac{(x_2 + y)/\sigma_v}{\sigma_v}\right) dx_2 \quad (\text{A.3.16})$$

In which $f_u(\cdot)$ is the marginal density of the truncated distribution (mean μ and variance σ_u^2); $f_v(\cdot)$ is the marginal density of a normal distribution (mean 0 and variance σ_v^2);

and $x_2 = \tau$. The pdf of the positive normal is: $f(x_2/\mu, \sigma_u, 0) = \frac{1}{\sigma} \frac{\phi\left(\frac{(x_2 - \mu)/\sigma_u}{[1 - \Phi\left(-\frac{\mu}{\sigma_u}\right)]}\right)}{[1 - \Phi\left(-\frac{\mu}{\sigma_u}\right)]}$.

¹⁰⁷ In addition, the parameter estimates are invariant to the equation dropped (output/input which is the normalizer) when the model is estimated by the maximum likelihood estimation method.

Following Stevenson (1980), the likelihood function for each y_i ($i = 1, \dots, T$) is:

$$\begin{aligned}
 f(y_i/\beta, \mu, \sigma_u, \sigma_v) &= \left(\frac{1}{\sqrt{2\pi\sigma^2}} \right) \exp \left\{ \frac{1}{2\sigma^2} (y_i - \beta'x_i - \mu)^2 \right\} \left[1 \right. \\
 &\quad \left. - \Phi \left(\frac{1}{\sigma} \left(-\frac{\mu}{\lambda} - (y_i - \beta'x_i)\lambda \right) \right) \right] \left[1 \right. \\
 &\quad \left. - \Phi \left(-\frac{\mu}{\lambda} (\lambda^{-2} + 1)^{\frac{1}{2}} \right) \right]^{-1}
 \end{aligned} \tag{A.3.17}$$

In which $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$ e $\lambda = \frac{\sigma_u}{\sigma_v}$.

The log-likelihood function for each y_i ($i = 1, \dots, n$) is:

$$\begin{aligned}
 \ln L(\beta, \mu, \sigma_u, \sigma_v) &= -\frac{1}{2} \ln(2\pi) - \frac{1}{2} \ln(\sigma_u^2 + \sigma_v^2) - \frac{1}{2(\sigma_u^2 + \sigma_v^2)} (y_i - \beta'x_i - \mu)^2 \\
 &\quad + \ln \left[1 - \Phi \left((\sigma_u^2 + \sigma_v^2)^{-\frac{1}{2}} \left(-\frac{\mu\sigma_v}{\sigma_u} - (y_i - \beta'x_i) \frac{\sigma_u}{\sigma_v} \right) \right) \right] \\
 &\quad - \ln \left[1 - \Phi \left(-\frac{\mu}{(\sigma_u^2 + \sigma_v^2)^{\frac{1}{2}}} \left(\left(\frac{\sigma_u}{\sigma_v} \right)^{-2} + 1 \right)^{\frac{1}{2}} \right) \right]
 \end{aligned} \tag{A.3.18}$$

Assuming independence among the observations, the above log-likelihood is implemented in Stata and the translog profit frontier can be estimated.

APPENDIX A.3.5: RESULTS FROM THE ESTIMATED PROFIT EQUATION

Table A.3.3 shows the complete estimations of the profit frontier equation. In order to understand the specific effects of the variables, the elasticities can be calculated.

Table A.3.3: Complete results, profit frontier, Models (1) to (5), 2006 Census.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent variable: ln(profits)					
Price(soybeans)	4.733***	-1.902	2.960***	-14.29***	-19.68***
Price(maize)	-0.276	-0.889	-0.608	1.315	3.508*
Price(ot. annual)	0.201	0.127	0.398**	-0.964	-0.697
Price(coffee)	-2.383***	16.70***	-1.685***	1.487	5.140*
Price(ot. perennial)	-0.0371	-3.037*	0.292	1.245	-0.160
Price(milk)	-0.621	-11.11***	-0.670	6.197*	4.067
Price(wood)	-0.707**	-1.873	-0.934***	-3.114	-3.204**
Price(beef)	-0.591	-0.919	0.122	4.826	10.23***
Price(ot. for)	0.132	0.535	0.266	1.705	-0.223
Price(fertil.)	0.386***	3.158***	0.520***	1.241*	0.916
Q(Fuel)				0.000297***	
Q(land)				-9.46e-06	
Irrig. area				-0.865	
GTO/Cert. seeds				1.127	
Conf. cattle				-12.17	
tilled				1.528	
Mech. harvesting				0.541	
Rainfall(summer)		-0.121***		-0.00490	
Rainfall(winter)		0.0633*		0.0293	
Temper.(summer)		-5.676**		5.322**	
Temper.(winter)		4.213***		-1.983**	
Price(soybeans)_Price(soybeans)	1.517**	2.032***	0.377	0.862	0.414
Price(soybean)_Price(maize)	0.395	0.588	-0.0342	0.0259	0.241
Price(soybeans)_Price(ot. annual)	-0.264*	-0.415***	0.0186	0.0556	0.0655
Price(soybean)_Price(coffee)	-1.533**	-1.776**	-0.819	-2.241***	-1.163*
Price(soybean)_Price(ot. perennial)	-0.754**	-0.394	0.153	0.257	0.212
Price(soybean)_Price(milk)	-0.296	-0.686	-0.192	0.583	0.191
Price(soybean)_Price(wood)	-0.779***	-0.865***	-0.297	-0.828***	-0.774***
Price(soybean)_Price(beef)	1.457***	0.867	0.404	0.532	0.778*
Price(soybean)_Price(ot. for)	-0.744***	-0.719***	0.179	0.145	-0.0206
Price(soybean)_Price(fertile.)	-0.0996	-0.207*	-0.175*	-0.243***	-0.291***
Price(maize)_Price(maize)	0.145*	0.0838	0.0523	0.0626	0.117

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Price(maize)_Price(ot. annual)	-0.115*	-0.114*	0.0116	0.0305	-0.0306
Price(maize)_Price(coffee)	-0.446**	-0.393*	-0.00995	0.268	0.0824
Price(maize)_Price(ot. perennial)	0.0712	0.0441	0.0645	-0.0527	0.0249
Price(maize)_Price(milk)	-0.307*	-0.169	-0.382**	-0.581***	-0.521***
Price(maize)_Price(wood)	0.241**	0.115	0.146*	0.116	0.0628
Price(maize)_Price(beef)	0.0773	-0.0999	0.124	0.0584	0.0159
Price(maize)_Price(ot. for)	-0.106	-0.0776	0.0380	0.0622	-0.000554
Price(maize)_Price(fertil.)	-0.0614	-0.0686*	-0.0215	-0.0215	-0.0408
Price(ot. annual)_Price(ot. annual)	0.210***	0.200***	0.0854***	0.0705***	0.104***
Price(ot. annual)_Price(coffee)	0.367***	0.196**	0.121	0.0393	0.0270
Price(ot. annual)_Price(ot. perennial)	0.128***	0.114**	0.0224	-0.0272	0.0116
Price(ot. annual)_Price(milk)	-0.402***	-0.105	-0.148*	-0.0548	-0.246***
Price(ot. annual)_Price(wood)	-0.101**	-0.140**	-0.177***	-0.106*	-0.162***
Price(ot. annual)_Price(beef)	-0.181**	-0.0837	-0.215***	-0.207**	-0.0929
Price(ot. annual)_Price(ot. for)	0.109**	0.0780	0.158***	0.122***	0.207***
Price(ot. annual)_Price(fertil.)	0.0734***	0.0933***	0.0567***	0.0425**	0.0469**
Price(coffee)_Price(coffee)	0.865***	0.593**	0.427**	1.108***	0.566***
Price(coffee)_Price(ot. perennial)	-0.311*	-0.282	-0.223	-0.142	-0.200
Price(coffee)_Price(milk)	-0.279	0.297	0.0498	-0.657**	-0.0975
Price(coffee)_Price(wood)	0.182	0.299	0.0890	0.274*	0.168
Price(coffee)_Price(beef)	-0.0705	-0.113	-0.115	0.0866	-0.106
Price(coffee)_Price(ot. for)	0.172	0.560***	0.00776	0.172	0.175
Price(coffee)_Price(fertil.)	0.0514	-0.0378	-0.0122	-0.0158	0.00943
Price(ot. perennial)_Price(ot. perennial)	0.322***	0.144**	0.209***	0.147**	0.220***
Price(ot. perennial)_Price(milk)	-0.0520	-0.0608	-0.248*	-0.214	-0.282*
Price(ot. perennial)_Price(wood)	0.274***	0.130	0.0386	0.0603	0.0986
Price(ot. perennial)_Price(beef)	-0.0914	0.0834	-0.166	-0.114	-0.298*
Price(ot. perennial)_Price(ot. for)	0.0176	0.0114	-0.0669	-0.0633	-0.0420
Price(ot. perennial)_Price(fertil.)	0.000213	0.0329	0.00485	0.00609	-0.00421
Price(milk)_Price(milk)	0.607***	0.124	0.204	0.462***	0.436**
Price(milk)_Price(wood)	0.0578	0.0551	0.0666	-0.111	0.0540
Price(milk)_Price(beef)	-0.0755	0.334	0.612**	0.0721	0.0661
Price(milk)_Price(ot. for)	0.0723	-0.230*	-0.168*	-0.154	-0.149
Price(milk)_Price(fertil.)	-0.0738	0.0609	-0.0692	0.00476	0.00276
Price(wood)_Price(wood)	0.128***	0.149***	0.0979***	0.0904***	0.129***
Price(wood)_Price(beef)	0.131	0.287*	0.192	0.657***	0.582***
Price(wood)_Price(ot. for)	-0.231***	-0.116	-0.137***	-0.190***	-0.199***
Price(wood)_Price(fertil.)	-0.0201	-0.0576	-0.0178	-0.00931	-0.0217
Price(beef)_Price(beef)	-0.905***	-0.832***	-0.465***	-0.471***	-0.544***
Price(beef)_Price(ot. for)	0.429***	0.267*	-0.0653	-0.221*	-0.110
Price(beef)_Price(fertil.)	0.0439	0.0601	0.138***	0.122**	0.191***
Price(ot. for)_Price(ot. for)	0.186***	0.138***	0.0664***	0.0761***	0.0856***

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Price(ot. for)_Price(fertil.)	-0.0706**	-0.0492*	-0.0454*	-0.000529	-0.0403
Price(fertil.)_Price(fertil.)	0.0390***	0.0482***	0.0485***	0.0451***	0.0498***
Q(Fuel)_Q(Fuel)			-2.47e-10***	-3.25e-10***	
Q(Fuel)_Q(land)			-1.19e-10***	-1.62e-10***	
Q(Fuel)_Irrig. area			-2.32e-05	-5.46e-05	
Q(Fuel)_GTO/Cert. seeds			8.34e-07	-4.06e-06	
Q(Fuel)_Conf. cattle			-4.34e-05	-3.50e-05	
Q(Fuel)_tilled			-7.87e-05***	-6.29e-05***	
Q(Fuel)_Mech. harvesting			6.10e-05***	2.07e-05	
Q(Fuel)_Rainfall(summer)				1.11e-08	
Q(Fuel)_Rainfall(winter)				-1.42e-07	
Q(Fuel)_Temper.(summer)				-1.21e-05**	
Q(Fuel)_Temper.(winter)				5.35e-06**	
Q(land)_Q(land)			-0	-0*	
Q(land)_Irrig. Area			1.14e-05	1.43e-05	
Q(land)_GTO/Cert. seeds			-2.85e-06**	-2.26e-06*	
Q(land)_Conf. cattle			2.14e-05***	1.68e-05**	
Q(land)_tilled			2.57e-05***	2.37e-05***	
Q(land)_Mech. harvesting			-4.44e-06**	-2.81e-07	
Q(land)_Rainfall(summer)				-4.08e-08***	
Q(land)_Rainfall(winter)				-6.44e-11	
Q(land)_Temper.(summer)				1.19e-06	
Q(land)_Temper.(winter)				-3.63e-07	
Irrig. area_Irrig. area			-7.397***	-7.105***	
Irrig. area_GTO/Cert. seeds			0.690	3.583**	
Irrig. area_Conf. cattle			-3.027	-4.978	
Irrig. area_tilled			-5.461	-6.256	
Irrig. area_Mech. harvesting			-4.484	-4.784	
Irrig. area_Rainfall(summer)				-0.0720***	
Irrig. area_Rainfall(winter)				-0.0292***	
Irrig. area_Temper.(summer)				-0.917	
Irrig. area_Temper.(winter)				1.107***	
GTO/Cert. seeds_GTO/Cert. seeds			0.0864	0.00669	
GTO/Cert. seeds_Conf. cattle			-4.015***	-3.365***	
GTO/Cert. seeds_tilled			0.0118	0.160	
GTO/Cert. seeds_Mech. harvesting			0.459	0.151	
GTO/Cert. seeds_Rainfall(summer)				0.00123	
GTO/Cert. seeds_Rainfall(winter)				-0.0126***	
GTO/Cert. seeds_Temp.(summer)				0.0435	
GTO/Cert. seeds_Temp.(winter)				-0.0331	
Conf. cattle_Conf. cattle			-2.739***	-2.265***	

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Conf. cattle_tilled			0.765	-0.0888	
Conf. cattle_Mech. harvesting			-2.650**	-2.090*	
Conf. cattle_Rainfall(summer)				0.0134	
Conf. cattle_Rainfall(winter)				0.00184	
Conf. cattle_Temper.(summer)				0.485	
Conf. cattle_Temper.(winter)				-0.184	
tilled_tilled			-1.469**	-1.734***	
tilled_Mech. harvesting			-2.621**	-2.184*	
tilled_Rainfall(summer)				-0.00473	
tilled_Rainfall(winter)				0.00172	
tilled_Temper.(summer)				0.232	
tilled_Temper.(winter)				-0.139	
Mech. harvesting_Mech. harvesting			-2.530***	-2.308***	
Mech. harvesting_Rainfall(summer)				-0.00179	
Mech. harvesting_Rainfall(winter)				-0.00280	
Mech. harvesting_Temper.(summer)				0.332	
Mech. harvesting_Temper.(winter)				-0.255*	
Rainfall(summer)_Rainfall(summer)		3.08e-05**		-5.28e-06	
Rainfall(summer)_Rainfall(winter)		-1.87e-05		-9.98e-06	
Rainfall(summer)_Temp.(summer)		0.00691***		9.49e-05	
Rainfall(summer)_Temp.(winter)		-0.00296***		-9.10e-05	
Rainfall(winter)_Rainfall(winter)		-4.11e-05***		-3.30e-05***	
Rainfall(winter)_Temp.(summer)		-0.00314		-0.00146	
Rainfall(winter)_Temp.(winter)		8.73e-05		4.71e-06	
Temper.(summer)_Temp.(summer)		0.229***		-0.167***	
Temper.(summer)_Temp.(winter)		-0.240***		0.144***	
Temper.(winter)_Temp.(winter)		0.0413***		-0.0406***	
Price(soybean)_Q(Fuel)			-9.64e-05***	-6.10e-05***	-9.42e-06
Price(soybean)_Q(land)			-1.09e-06	2.31e-07	-5.19e-06**
Price(soybean)_Irrig. area			5.603**	4.938*	6.343**
Price(soybean)_GTO/Cert. seeds			-0.0932	-0.840	-0.962**
Price(soybean)_Conf. cattle			2.120	0.715	3.705**
Price(soybean)_tilled			1.193	1.818	-0.957
Price(soybean)_Mech. harvesting			0.155	0.501	0.915
Price(soybean)_Rainfall(summer)		0.00803*		0.0200***	0.0237***
Price(soybean)_Rainfall(winter)		-0.00140		0.00252	0.0118***
Price(soybean)_Temper.(summer)		0.242		1.127***	1.208***
Price(soybean)_Temper.(winter)		0.00113		-0.490***	-0.464***
Price(maize)_Q(Fuel)			7.77e-06	7.99e-06	1.83e-05**
Price(maize)_Q(land)			1.05e-06	6.54e-07	1.79e-06**
Price(maize)_Irrig. area			4.723***	0.825	3.948***
Price(maize)_GTO/Cert. seeds			0.0409	0.111	-0.114

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Price(maize)_Conf. cattle			-0.155	0.202	-0.460
Price(maize)_tilled			-0.781**	-0.723**	-0.835**
Price(maize)_Mech. harvesting			-0.188	-0.586	-0.177
Price(maize)_Rainfall(summer)	-0.00174			-0.000156	-0.000459
Price(maize)_Rainfall(winter)	0.000218			0.00111	0.00106
Price(maize)_Temper.(summer)	0.0990			-0.135	-0.207**
Price(maize)_Temper.(winter)	-0.0637			0.0503	0.0460
Price(ot. annual)_Q(Fuel)			8.49e-06***	1.24e-05***	1.02e-05***
Price(ot. annual)_Q(land)			-1.82e-06***	-1.40e-06***	-2.99e-06***
Price(ot. annual)_Irrig. area			-1.541***	-1.230***	-1.458***
Price(ot. annual)_GTO/Cert. seeds			0.297***	0.405***	0.402***
Price(ot. annual)_Conf. cattle			0.00913	0.0648	-0.301
Price(ot. annual)_tilled			-0.310*	-0.289	-0.178
Price(ot. annual)_Mech. harvesting			-0.182	-0.186	-0.172
Price(ot. annual)_Rainfall(summer)	-0.000962			-0.00106	-9.83e-07
Price(ot. annual)_Rainfall(winter)	-0.00387***			-0.00255***	-0.00179***
Price(ot. annual)_Temper.(summer)	0.0906*			0.105**	0.0671
Price(ot. annual)_Temper.(winter)	-0.0669***			-0.0520**	-0.0183
Price(coffee)_Q(Fuel)			3.82e-05***	-1.46e-06	5.52e-06
Price(coffee)_Q(land)			2.45e-06***	1.92e-06	2.38e-06***
Price(coffee)_Irrig. area			2.866**	8.891***	3.992***
Price(coffee)_GTO/Cert. seeds			-0.176	-0.585	0.0720
Price(coffee)_Conf. cattle			0.562	1.654	0.358
Price(coffee)_tilled			0.232	-1.359	-0.313
Price(coffee)_Mech. harvesting			0.461	0.371	-0.173
Price(coffee)_Rainfall(summer)	-0.00254			-0.00202	-0.00547***
Price(coffee)_Rainfall(winter)	0.00744***			0.00460*	-0.000131
Price(coffee)_Temper.(summer)	-0.816***			-0.295	-0.264*
Price(coffee)_Temper.(winter)	0.0385			0.0881	0.000645
Price(ot. perennial)_Q(Fuel)			2.10e-05***	1.43e-05***	2.46e-06
Price(ot. perennial)_Q(land)			-6.01e-07	-4.76e-07	-2.96e-07
Price(ot. perennial)_Irrig. area			-1.551	-1.260	-1.859*
Price(ot. perennial)_GTO/Cert. seeds			-0.219	-0.00481	0.126
Price(ot. perennial)_Conf. cattle			0.193	0.143	-0.0188
Price(ot. perennial)_tilled			-0.00941	0.269	-0.0856
Price(ot. perennial)_Mech. harvesting			0.785**	0.742**	0.813**
Price(ot. perennial)_Rainfall(summer)	0.000450			-0.00331***	-0.00210*
Price(ot. perennial)_Rainfall(winter)	-0.00136			-0.00229*	-0.000178
Price(ot. perennial)_Temper.(summer)	0.209**			-0.0451	0.00135

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Price(ot. peren)_temper.(winter)	-0.0876**			0.0243	0.0234
Price(milk)_Q(Fuel)			-1.22e-05	-2.02e-05**	-3.93e-05***
Price(milk)_Q(land)			3.87e-06***	3.80e-06***	6.16e-06***
Price(milk)_Irrig. area			-1.151	-5.331***	-0.451
Price(milk)_GTO/Cert. seeds			0.208	0.548**	0.393
Price(milk)_Conf. cattle			-1.115	-0.921	-0.421
Price(milk)_tilled			0.815	1.294**	1.777***
Price(milk)_Mech. harvesting			-0.843	0.331	-1.002
Price(milk)_Rainfall(summer)	-0.00311			-0.00933***	-0.00893***
Price(milk)_Rainfall(winter)	-0.00370			-0.00597***	-0.00827***
Price(milk)_Temper.(summer)	0.440**			-0.203	-0.151
Price(milk)_Temper.(winter)	0.0149			0.0805	0.0495
Price(wood)_Q(Fuel)			1.70e-05***	8.20e-06	1.94e-05***
Price(wood)_Q(land)			8.29e-08	-6.26e-07	2.88e-07
Price(wood)_Irrig. area			-0.608	0.760	-1.913***
Price(wood)_GTO/Cert. seeds			0.282**	0.201	0.241*
Price(wood)_Conf. cattle			0.686	0.510	-0.388
Price(wood)_tilled			0.0672	-0.186	0.203
Price(wood)_Mech. harvesting			0.253	-0.624	0.0948
Price(wood)_Rainfall(summer)	0.00214			0.00218*	0.000760
Price(wood)_Rainfall(winter)	0.00221			0.00218*	-0.00221***
Price(wood)_Temper.(summer)	-0.0701			0.0727	0.0806
Price(wood)_Temper.(winter)	0.0857*			0.00315	0.00631
Price(beef)_Q(Fuel)			2.93e-05**	4.86e-05***	9.53e-06
Price(beef)_Q(land)			-2.30e-06	-3.25e-06**	1.02e-06
Price(beef)_Irrig. area			-8.092***	-6.291***	-7.300***
Price(beef)_GTO/Cert. seeds			-0.340	0.286	-0.147
Price(beef)_Conf. cattle			-2.422**	-2.072*	-2.143*
Price(beef)_tilled			-0.718	-0.496	0.499
Price(beef)_Mech. harvesting			-0.941*	-1.013*	-0.659
Price(beef)_Rainfall(summer)	0.000572			-0.00370*	-0.00579***
Price(beef)_Rainfall(winter)	-0.000346			0.000817	0.00171
Price(beef)_Temper.(summer)				-0.484***	-0.726***
Price(beef)_Temper.(winter)				0.272***	0.352***
Price(ot. for)_Q(Fuel)			6.38e-07	-3.13e-06	4.93e-06
Price(ot. for)_Q(land)					-1.85e-06***
Price(ot. for)_Irrig. area			-4.82e-07	-5.12e-07	0.708
Price(ot. for)_GTO/Cert. seeds			1.138**	-0.00575	-0.0711
Price(ot. for)_Conf. cattle			-0.0410	-0.0514	-0.0711
Price(ot. for)_tilled			0.152	0.0177	0.148
Price(ot. for)_Mech. harvesting			0.199	0.174	0.308
			0.491	0.262	0.0478

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Price(ot. for)_Rainfall(summer)		-0.00182*		-0.000970	-0.000276
Price(ot. for)_Rainfall(winter)		0.00223**		0.00127	0.000872
Price(ot. for)_Temper.(summer)		-0.107		-0.0835	0.0125
Price(ot. for)_Temper.(winter)		0.0783**		0.0340	0.0113
Price(fertil.)_Q(Fuel)			-1.89e-06	8.09e-07	-6.90e-06***
Price(fertil.)_Q(land)			-1.08e-06***	-6.60e-07**	-4.84e-07*
Price(fertil.)_Irrig. area			-1.335***	-1.803***	-1.728***
Price(fertil.)_GTO/Cert. seeds			-0.0233	-0.104	-0.0532
Price(fertil.)_Conf. cattle			-0.157	-0.307	-0.499**
Price(fertil.)_tilled			-0.757***	-0.670***	-0.648***
Price(fertil.)_Mech. harvesting			-0.0971	-0.00700	0.0491
Price(fertil.)_Rainfall(summer)		-0.00152***		-0.000611	-0.000440
Price(fertil.)_Rainfall(winter)		-0.000615		-0.000315	-0.000824**
Price(fertil.)_Temper.(summer)		-0.105***		-0.0174	-0.000627
Price(fertil.)_Temper.(winter)		0.0189		-0.0130	-0.0120
Constant	12.46***	35.16	12.57***	-30.36	13.01***
Insig2v	-0.0582	-0.164***	-0.656***	-0.809***	-0.750***
Insig2u	0.446***	0.430***	-0.142	-0.175*	0.0936
Log-likelihood	-8619.94	-8425.81	-5981.51	-5735.41	-6062.33
Observations	5,319	5,319	4,520	4,520	4,520

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Next table shows the price elasticities calculated at the sample mean. The price elasticities of supply show some interesting results, such as the high substitutability from rural markets in general to other annual crops. The negative cross-price elasticities indicate that, when the market is good for other crops, producers replace other annual crops for other agricultural products and vice-versa, which means that when prices are lower for other crops other annual crops are chosen by farmers.

The own-price elasticities of supply are higher than one and significant for other perennial crops, coffee, milk and forest products (wood and others), indicating that the production of those agricultural products is highly sensitive to prices. One explanation could be the long-term decisions involved in most of these products. Hence, farmers seem to be more sensitive to price variations. Wunder (1999), in the analysis of extractivism in Brazil, comments on the high elasticity of supply for forest-extracted products.

Table A.3.4: Price elasticities of supply, estimates and statistical significance information, Model 5.

Price elasticities - Model 5	Other perennial crops	Other annual crops	Soybeans	Maize	Coffee	Beef	Milk	Other forest prod.	Wood
Other perennial crops	1.17**	-0.87***	0.07	-0.7	-2.86	-6.73**	-2.46***	-15.59	30.6
Other annual crops	-0.45	-0.32***	-0.26	-0.79*	-0.29	-2.38	-1.92***	71.94***	-52.3***
Soybeans	1.21	-0.63**	1.1	1.06	-12.24**	14.49	0.28	-7.97	-247.86***
Maize	-0.64	-0.94***	0.22	0.02	-0.06	-0.56	-3.76***	-1.06	19.19
Coffee	-2.77	-0.84***	-6.17**	-0.27	4.68**	-2.98	-1.44	60.35	52.79
Beef	-3.74**	-1.16***	2.57	-0.83	-1.99	-11.62***	-0.58	-39.24	185***
Milk	-3.46**	-1.37***	0.04	-4.79***	-1.78	0.48	1.6*	-52.9	16.42
Other forest prod.	-1.39**	-0.53***	-1.09	-1	0.73	-3.15	-1.82***	28.91***	-64.45***
Wood	-0.07	-1.36***	-4.5***	-0.52	0.66	10.43***	-0.7	-70.43***	40.29***

*** p<0.01, ** p<0.05, * p<0.10.

Table A.3.5 shows the summary of the average effects calculated for municipalities that had no production of the specific crop: $\frac{\partial \ln(\widehat{q_{jl}})}{\partial Z_{jl}^1} = \left(\sum_{j>1} \hat{\nu}_{jr} \ln(p_{ji}) / \ln(p_{1i}) + \frac{\hat{\nu}_{jr}}{\hat{s}_{jl}} \right)$, if $s_{ji} = 0$. This measurement shows how production would expand based on the effects calculated and positive or negative variations of the climate variables:

Table A.3.5: Expected expansion of production for municipalities with no previous production

Outputs (j)	Summer		Winter	
	Expected positive expansion if $\Delta Z < 0^*$	Expected positive expansion if $\Delta Z > 0^*$	Expected positive expansion if $\Delta Z < 0^*$	Expected positive expansion if $\Delta Z > 0^*$
<i>Rainfall effect (Z)</i>				
Soybeans	0.21%	52.65%	1.18%	51.68%
Maize	5.82%	19.14%	4.88%	20.08%
Other annual crops	8.56%	22.46%	31.02%	0.00%
Coffee	35.53%	4.23%	3.01%	36.75%
Other peren. crops	40.77%	8.96%	19.78%	29.95%
Milk	17.70%	2.88%	13.99%	6.58%
Wood	2.84%	14.55%	10.98%	6.42%
Beef	0.48%	0.00%	0.00%	0.48%
Other forest products	19.51%	57.16%	5.94%	70.73%
<i>Temperature effect (Z)</i>				
Soybeans	0.17%	52.69%	48.58%	4.27%
Maize	19.51%	5.44%	0.38%	24.58%
Other annual crops	0.00%	31.02%	6.95%	24.06%
Coffee	20.21%	19.56%	3.06%	36.70%
Other peren. crops	4.48%	45.25%	2.73%	46.99%
Milk	0.41%	20.16%	0.82%	19.75%
Wood	0.78%	16.61%	2.03%	15.36%
Beef	0.48%	0.00%	0.00%	0.48%
Other forest products	7.51%	69.16%	3.71%	72.96%

* Measured in % of municipalities (out of the municipalities with current null production of the culture).

Figure A.3.2: Expected CC effect on production, temperature, Scenario B2 (2040-2069)

Figure A.3.2: Expected CC effect on production, temperature, Scenario B2 (2040-2069) (cont.)

APPENDIX A.4.1: WEATHER OBSERVATION IN 2005 AND 2006 BY MUNICIPALITIES

Figure A.4.1: Monthly rainfall deviation from the long-term average, 2006, by season, in mm

Figure A.4.2: Monthly rainfall deviation from the long-term average, 2005, by season, in mm

Figure A.4.3: Monthly temperature deviation from the long-term average, 2006, by season, in °C.

Figure A.4.4: Monthly temperature deviation from the long-term average, 2005, by season, in °C.

APPENDIX A.4.2: WEATHER INDEX INSURANCE DISCUSSION

Weather index insurance reduces many market failures when compared to traditional agricultural insurances. This reduction considers: lower transaction costs (as it is based on objective measures¹⁰⁸, calculated from publicly available data, leading to more rapid payouts¹⁰⁹); reduced adverse selection (less hidden information between farmers and insurers about the risk exposure); and less moral hazard (insurers cannot modify their risk exposure). Moreover, this mechanism allows producers to save part of their production, since nowadays insurance companies take a long time to visit affected farms and do not allow salvaging the unaffected part of the production.¹¹⁰ Another important piece of information is about how much farmers spend to avoid risks. Gautam *et al.* (1994) showed some evidence that farmers often sacrifice 10-20% of their income by using traditional risk management strategies.

However, the disadvantages of this method were highlighted by Hellmuth *et al.* (2009):

- I) *It is a new tool and it has some learning costs:* if the mechanism is proven to be effective after some time, this disadvantage can be minimized.
- II) *It is vulnerable to basis risk* (loss without payouts, or payout with no loss): The risk vulnerability can also be mitigated by contract design.
- III) *The definition of a threshold for the index can be difficult:* The definition of threshold can be solved by daily monitoring, and the achievement of a threshold by some consecutive days, for example.

Barnett and Mahul (2007) believe that this type of index insurance can be an effective alternative if it offers transparency and acceptability to all parties. Therefore, it is important to check the robustness of the method. Governments should be involved in the mechanism design by establishing an appropriate legal and regulatory framework to take maximum advantage of the potential of this kind of index, and also by publicizing the information to farmers

¹⁰⁸ The requirements for such approach, following Barnett and Mahul (2007), would be: the availability of accurate historical weather data; correlation between available weather variables and realized losses; and time periods in which losses are most likely to occur.

¹⁰⁹ The claims adjuster does not need to visit the farms to assess the losses, as the payout is related to objective criteria.

¹¹⁰ Normally farmers can use the unaffected part to feed animals, for example.

A contract based on index insurance can serve many actors of the agricultural sector, such as small farmers and agricultural laborers; suppliers and financiers, business in the agricultural supply chain and NGOs, among others.

The index insurance mechanism must have a threshold defined in order to limit the range of values over which the payout will be made. When the threshold is reached, the payout increases proportionately as the value reaches the limit (SKEES, 2008). Moreover, the amount of the payout will also depend on the amount of insurance purchased. The author presents an illustrative example for the calculation of index insurance for droughts that begins the payouts when rainfall is below a threshold:

Index: Total accumulated rainfall (R) measured at a weather station i , in millimeters (mm) = R_i

Threshold: R_i^T

Limit: R_i^L , where $R_i^L < R_i^T$

Insurance Purchased (I): \$ I

Payment Rate (PR): Based on the difference between the actual value (R_i^A) and the threshold and limit:

$$PR = \frac{(R_i^T - R_i^A)}{(R_i^T - R_i^L)} \quad (\text{A.4.1})$$

Payout (PO): Payment Rate multiplied by the Insurance Purchased:

$$PO = \frac{(R_i^T - R_i^A)}{(R_i^T - R_i^L)} * I \quad (\text{A.4.2})$$

According to Skees (2008), besides its simplicity, this type of index insurance can be effective to prevent all the problems involving traditional rural insurance, such as moral hazard, transaction costs, adverse selection, lack of transparency, and delay in receiving payouts, among others.