Climate change impact on crop yield: towards a probabilistic modeling framework

Winkler, Jordan
Dissertation

CLIMATE CHANGE IMPACT ON CROP YIELD: TOWARDS A PROBABILISTIC MODELING FRAMEWORK

by

JORDAN R. WINKLER
B.S., Clarkson University, 2005

Submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy
2015
First Reader

Ian Sue Wing, Ph.D.
Associate Professor of Earth and Environment

Second Reader

Mark Friedl, Ph.D.
Professor of Earth and Environment

Third Reader

Dana Bauer, Ph.D.
Assistant Professor of Earth and Environment
The earth is not a mechanism but an organism, a being with its own life and its own reasons, where the support and sustenance of the human animal is incidental. If man in his newfound power and vanity persists in the attempt to remake the planet in his own image, he will succeed only in destroying himself, not the planet. The earth will survive our most ingenious folly.

Edward Abbey
Acknowledgements

Throughout the course of this work I have been fortunate to have the help of many supportive and talented individuals. I would like to take this opportunity to thank those who have supported me along this journey, as well as those who have contributed to the scope, development, and execution of this work.

To my advisor Ian Sue Wing for taking me on as a student and instilling a rigor and focus in my work. Your methodological approach was invaluable in helping me work through the early stages of this project and ultimately in helping me find a meaningful storyline in my research. I am also thankful for your patience and support for my rather non-traditional path towards this end.

So many people at Boston University provided critical guidance and support. To Robert Kaufmann and Cutler Cleveland for giving me the opportunity to assist in teaching their wonderful course. To Suchi Gopal for also supporting my big ideas. To Mark Friedl and Dana Bauer for their work as my committee members.

I received significant support from the National Center for Atmospheric Research. Thanks to Steve Sain for supporting my initial visiting position at NCAR, which represented a turning point in my dissertation progress. I am infinitely grateful to Claudia Tebaldi and Doug Nychka, who’s guidance and teaching brought my work into focus.

It feels infinitely impossible to express my gratitude for my family’s support. To my step-father for his calm and reasoned support. To my sister for her love and care. To Kate, who saw me through many late nights. To Madison, who has taught me more about the virtues of patience and consistency than any human. Lastly, to my beautiful mother. Your strength and light will continue to inspire me to be a better man. I dedicate this work to you. May your memory be for a blessing.
CLIMATE CHANGE IMPACT ON CROP YIELD: TOWARDS A PROBABILISTIC MODELING FRAMEWORK

JORDAN R. WINKLER

Boston University Graduate School of Arts and Sciences, 2015
Major Professor: Ian Sue Wing, Professor of Earth and Environment

ABSTRACT

Climate change presents a clear threat to the future of global food security. Changes in the patterns of temperature and precipitation have the potential to greatly decrease agricultural production. Developing successful adaptation strategies is dependent on understanding both the potential changes in yield of a given crop, as well as the likelihood those changes occurring. This requires an understanding of the uncertainty in the geographic patterns of future climate change, as well as the response of a crop to those changes. In this dissertation I explore a framework for generating rapid estimates of the risk of climate change to agricultural yields.

Using data from multiple climate models I use a regression based pattern scaling approach in conjunction with a multi-resolution Gaussian spatial process model to emulate the output of a multi-model ensemble of global climate models. The approach is flexible across climate scenarios, allowing it to be easily used in conjunction with other impact models. Using this model I am able to rapidly emulate thousands of runs of a climate model on a laptop computer. The resulting synthetic distributions retain the spatial variability of the initial emulated models and provide a tool for generating probabilistic forecasts of regional climate change.

Next I use a generalized additive model approach to estimate the stable manifold yield
response surface of a set of irrigated and rained crops in China. This approach highlights the nonlinear relationship between changes in temperature and precipitation and yield. Results suggest that irrigation alone cannot prevent losses from climate change. Predictions of future temperature and precipitation show a trend towards temperatures above the critical threshold for many crops, indicating the potential for large losses.

In the final chapter I combine the previously described methods to assess the impact of climate change on the spatial patterns of crop yield change in China. Result indicate overall losses to crop yield in the majority of cropped regions for both irrigated and non irrigated crops. These results represent a new methodology for rapidly assessing the risk of climate change to crop yield, and provide a new tool for prioritizing adaptation measures.
Contents

1 Introduction 1
  1.1 Global Assessments of Climate Change Impact on Agriculture 1
  1.2 Limits to Characterizing Risk in Existing Crop Impact Studies 4

2 Spatial Probability Distributions of Global Climate Models from a Multi-
  Model Ensemble 8
  2.1 Introduction 8
  2.2 The Pattern Scaling Technique 10
  2.3 Methods 15
    2.3.1 Data Preprocessing 15
    2.3.2 Calculating Patterns 16
    2.3.3 Calculating Residuals 17
    2.3.4 A Spatial Model for Residuals 19
  2.4 Results 22
    2.4.1 Global Patterns of Temperature and Precipitation 23
    2.4.2 Global Risk of Temperature and Precipitation Change 23
    2.4.3 Discussion 26
  2.5 Conclusions 27

3 Crop Yield Response to Temperature and Precipitation Change in China 47
  3.1 Introduction 47
    3.1.1 Background 48
  3.2 Methodology 53
    3.2.1 Crop Model Data 53
    3.2.2 Functional Form 54
    3.2.3 Exposure Plots 55
B.1.1 Irrigated Yield Response .......................... 198

References .......................... 250

Curriculum Vitae .......................... 258
List of Tables

3.1 Non-irrigated Corn Log Yield Response by Quantile .......................... 71
3.2 Non-irrigated Soybean Log Yield Response by Quantile ......................... 71
3.3 Non-irrigated Rice Log Yield Response by Quantile ............................. 71
3.4 Non-irrigated Millet Log Yield Response by Quantile ........................... 72
3.5 Non-irrigated Sorghum Log Yield Response by Quantile ......................... 72
3.6 Non-irrigated Potato Log Yield Response by Quantile .......................... 72
3.7 Irrigated Corn Log Yield Response by Quantile .................................. 72
3.8 Irrigated Soybean Log Yield Response by Quantile ............................. 73
3.9 Irrigated Rice Log Yield Response by Quantile .................................. 73
3.10 Irrigated Millet Log Yield Response by Quantile ............................... 73
3.11 Irrigated Sorghum Log Yield Response by Quantile ............................ 73
3.12 Irrigated Potato Log Yield Response by Quantile .............................. 74

A.1 Spatial Model Parameters for Temperature ....................................... 129
A.2 Spatial Model Parameters for Precipitation ...................................... 129
A.3 Comparison of synthetic and empirical distribution functions for seasonal average temperature at two degrees global warming, DJF / MAM ............... 133
A.4 Comparison of synthetic and empirical distribution functions for seasonal average temperature at two degrees global warming, JJA / SON ...................... 134
A.5 Comparison of synthetic and empirical distribution functions for seasonal average temperature at three degrees warming, DJF / MAM ................. 135
A.6 Comparison of synthetic and empirical distribution functions for seasonal average temperature at three degrees warming, JJA / SON ...................... 136
A.7 Comparison of synthetic and empirical distribution functions for seasonal average precipitation at two degrees warming, JJA / SON ...................... 137
A.8 Comparison of synthetic and empirical distribution functions for seasonal average precipitation at two degrees warming, JJA / SON . . . . . . . . . . 138
A.9 Comparison of synthetic and empirical distribution functions for seasonal average precipitation at three degrees warming, DJF / MAM . . . . . . . . 141
A.10 Comparison of synthetic and empirical distribution functions for seasonal average precipitation at three degrees warming, JJA / SON . . . . . . . . 142
List of Figures

1.1 A Conceptual Framework of Yield Loss Risk ........................................... 6
1.2 Historical Approach to Crop Impact Assessment ................................. 7

2.1 Patterns of Seasonal Temperature Change ............................................. 29
2.2 Patterns of Seasonal Precipitation Change ........................................... 30
2.3 Temperature Risk Map at 2 degrees Global Warming - December, January, February ................................................................. 31
2.4 Temperature Risk Map at 2 degrees Global Warming - March, April, May ................................................................. 32
2.5 Temperature Risk Map at 2 degrees Global Warming - June, July, August ................................................................. 33
2.6 Temperature Risk Map at 2 degrees Global Warming - September, October, November ................................................................. 34
2.7 Temperature Risk Map at 3 degrees Global Warming - December, January, February ................................................................. 35
2.8 Temperature Risk Map at 3 degrees Global Warming - March, April, May ................................................................. 36
2.9 Temperature Risk Map at 3 degrees Global Warming - June, July, August ................................................................. 37
2.10 Temperature Risk Map at 3 degrees Global Warming - September, October, November ................................................................. 38
2.11 Precipitation Risk Map at 2 degrees Global Warming - December, January, February ................................................................. 39
2.12 Precipitation Risk Map at 2 degrees Global Warming - March, April, May ................................................................. 40
2.13 Precipitation Risk Map at 2 degrees Global Warming - June, July, August ................................................................. 41
2.14 Precipitation Risk Map at 2 degrees Global Warming - September, October, November ................................................................. 42
2.15 Precipitation Risk Map at 3 degrees Global Warming - December, January, February ................................................................. 43
2.16 Precipitation Risk Map at 3 degrees Global Warming - March, April, May ................................................................. 44
4.16 Soybean Yield Weighted Impact - Three Degrees Warming ............... 101
4.17 Rice Yield Weighted Impact - Two Degrees Warming ................. 102
4.18 Rice Yield Weighted Impact - Three Degrees Warming ............. 103
4.19 Sorghum Yield Weighted Impact - Two Degrees Warming .......... 104
4.20 Sorghum Yield Weighted Impact - Three Degrees Warming ....... 105
4.21 Millet Yield Weighted Impact - Two Degrees Warming .......... 106
4.22 Millet Yield Weighted Impact - Three Degrees Warming ......... 107
4.23 Potato Yield Weighted Impact - Two Degrees Warming .......... 108
4.24 Potato Yield Weighted Impact - Three Degrees Warming ......... 109

A.1 Regional Temperature Residuals from Pattern Scaling compared to Global
Mean Temperature Change .......................................................... 128
A.2 Regional Precipitation Residuals from Pattern Scaling compared to Global
Mean Temperature Change .......................................................... 130
A.3 Grid Cell Temperature Residuals from Pattern Scaling compared to Global
Mean Temperature Change .......................................................... 131
A.4 Regional Precipitation Residuals from Pattern Scaling compared to Global
Mean Temperature Change .......................................................... 132
A.5 Average Patterns of Seasonal Temperature Natural Variability ...... 139
A.6 Average Patterns of Seasonal Precipitation Natural Variability ...... 140
A.7 Regional Temperature Distributions at 2 and 3 Degrees Warming, Western
Hemisphere- December, January, February ...................................... 143
A.8 Regional Temperature Distributions at 2 and 3 Degrees Warming, Western
Hemisphere - March, April, May .................................................. 144
A.9 Regional Temperature Distributions at 2 and 3 Degrees Warming, Western
Hemisphere - June, July, August .................................................. 145
A.10 Regional Temperature Distributions at 2 and 3 Degrees Warming, Western
Hemisphere - June, July, August ................................................. 146
A.11 Regional Temperature Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - December, January, February 147
A.12 Regional Temperature Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - March, April, May 148
A.13 Regional Temperature Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - June, July, August 149
A.14 Regional Temperature Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - June, July, August 150
A.15 Regional Precipitation Distributions at 2 and 3 Degrees Warming, Western Hemisphere - December, January, February 151
A.16 Regional Precipitation Distributions at 2 and 3 Degrees Warming, Western Hemisphere - March, April, May 152
A.17 Regional Precipitation Distributions at 2 and 3 Degrees Warming, Western Hemisphere - June, July, August 153
A.18 Regional Precipitation Distributions at 2 and 3 Degrees Warming, Western Hemisphere - September, October, November 154
A.19 Regional Precipitation Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - December, January, February 155
A.20 Regional Precipitation Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - March, April, May 156
A.21 Regional Precipitation Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - June, July, August 157
A.22 Regional Precipitation Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - September, October, November 158
A.23 Regional Boundaries adopted from Giorgi and Mearns (2002) 159
A.24 Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming - December, January, February ............................... 160

A.25 Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming - December, January, February ............................... 161

A.26 Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming - March, April, May ......................................................... 162

A.27 Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming - March, April, May ......................................................... 163

A.28 Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming - June, July, August ............................................................. 164

A.29 Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming - June, July, August ............................................................. 165

A.30 Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming - September/October/December ........................................ 166

A.31 Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming - September/October/December ........................................ 167

A.32 Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 3° Warming - December, January, February .................................................. 168
<table>
<thead>
<tr>
<th>Regional Distributions</th>
<th>Synthetic Temperature Change</th>
<th>Compared to Histograms of Modeled Change</th>
<th>in the Eastern Hemisphere</th>
<th>at $3^\circ$ Warming</th>
<th>in the Western Hemisphere</th>
<th>at $3^\circ$ Warming</th>
<th>in the Eastern Hemisphere</th>
<th>at $3^\circ$ Warming</th>
<th>in the Western Hemisphere</th>
<th>at $3^\circ$ Warming</th>
<th>in the Eastern Hemisphere</th>
<th>at $3^\circ$ Warming</th>
<th>in the Western Hemisphere</th>
<th>at $2^\circ$ Warming</th>
</tr>
</thead>
<tbody>
<tr>
<td>Section</td>
<td>Page</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------------------------------------------------------------</td>
<td>------</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A.42 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming-March, April, May</td>
<td>178</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A.43 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming-March, April, May</td>
<td>179</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A.44 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming-June, July, August</td>
<td>180</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A.45 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming- June, July, August</td>
<td>181</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A.46 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 3° Warming- September/October/December</td>
<td>182</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A.47 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3° Warming- September/October/December</td>
<td>183</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A.48 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 3° Warming- December, January, February</td>
<td>184</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A.49 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3° Warming- December, January, February</td>
<td>185</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A.50 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 3° Warming-March, April, May</td>
<td>186</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
A.51 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3° Warming- March, April, May 187
A.52 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 3° Warming- June, July, August 188
A.53 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3° Warming- June, July, August 189
A.54 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 3° Warming- September/October/December 190
A.55 Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3° Warming- September/October/December 191
B.1 Non-Irrigated Yield Response: Soybean Early Growing Degree Days 202
B.2 Non-Irrigated Yield Response: Soybean Late Growing Degree Days 203
B.3 Non-Irrigated Yield Response: Soybean Early Precipitation 204
B.4 Non-Irrigated Yield Response: Soybean Late Precipitation 205
B.5 Non-Irrigated Yield Response: Rice Early Growing Degree Days 206
B.6 Non-Irrigated Yield Response: Rice Late Growing Degree Days 207
B.7 Non-Irrigated Yield Response: Rice Early Precipitation 208
B.8 Non-Irrigated Yield Response: Rice Late Precipitation 209
B.9 Non-Irrigated Yield Response: Millet Early Growing Degree Days 210
B.10 Non-Irrigated Yield Response: Millet Late Growing Degree Days 211
B.11 Non-Irrigated Yield Response: Millet Early Precipitation 212
B.12 Non-Irrigated Yield Response: Millet Late Precipitation 213
B.40 Irrigated Yield Response: Sorghum Late Precipitation ........................ 241
B.41 Irrigated Yield Response: Potato Early Growing Degree Days .............. 242
B.42 Irrigated Yield Response: Potato Late Growing Degree Days ............... 243
B.43 Irrigated Yield Response: Potato Early Precipitation ......................... 244
B.44 Irrigated Yield Response: Potato Late Precipitation ......................... 245
B.45 Irrigated Yield Response: Beans ...................................................... 246
B.46 Irrigated Yield Response: Beets ....................................................... 247
B.47 Irrigated Yield Response: Oats ......................................................... 248
B.48 Irrigated Yield Response: Winter Wheat ............................................. 249
### List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AEZ</td>
<td>Agro Ecological Zone</td>
</tr>
<tr>
<td>BLS</td>
<td>Basic Linked System</td>
</tr>
<tr>
<td>CMIP3</td>
<td>Third Coupled Model Intercomparison Project</td>
</tr>
<tr>
<td>CMIP5</td>
<td>Fifth Coupled Model Intercomparison Project</td>
</tr>
<tr>
<td>DJF</td>
<td>December, January, February</td>
</tr>
<tr>
<td>DNDC</td>
<td>DeNitrification DeComposition</td>
</tr>
<tr>
<td>ENSO</td>
<td>El Nino, Southern Oscillation</td>
</tr>
<tr>
<td>GAM</td>
<td>General Additive Model</td>
</tr>
<tr>
<td>GCM</td>
<td>Global Circulation Models</td>
</tr>
<tr>
<td>GDD</td>
<td>Growing Degree Day</td>
</tr>
<tr>
<td>GMRF</td>
<td>Gaussian Markov Random Field</td>
</tr>
<tr>
<td>GHG</td>
<td>Green House Gasses</td>
</tr>
<tr>
<td>ISI-MIP</td>
<td>Inter-Sectoral Impact Model Intercomparison Project</td>
</tr>
<tr>
<td>JJA</td>
<td>June, July, August</td>
</tr>
<tr>
<td>MAM</td>
<td>March, April, May</td>
</tr>
<tr>
<td>MERRA</td>
<td>Modern Era Retrospective Reanalysis for Research &amp; Applications</td>
</tr>
<tr>
<td>MIRCA</td>
<td>Monthly Irrigated and Rainfed Crop Areas</td>
</tr>
<tr>
<td>SCM</td>
<td>Simple Climate Models</td>
</tr>
<tr>
<td>SON</td>
<td>September, October, November</td>
</tr>
</tbody>
</table>
Chapter 1

Introduction

In recent years there has been growing concern over the impacts of climate change on crop yields, and the consequences for global food security. Today nearly 800 million individuals are living in a state of chronic food insecurity (FAO, 2014). The prospect of increased demand from a growing global population combined with the threat of climate change highlights the need for effective adaptation strategies. Adaptation measures, such as investments in increased irrigation or new cultivars, can help minimize the potential risk for yield losses. However, this risk is regionally heterogeneous, owing to differences in climate, soils and access to inputs to crop production. Successful adaptation depends on identifying regions that are at the highest risk. To understand the geographic distribution of this vulnerability, one must quantify the regionally differential effects of climate change on crop production, and the associated uncertainty. Understanding this process requires a consistent modeling framework that integrates the distribution of spatially correlated changes in climate variables with fine scale crop response functions.

1.1 Global Assessments of Climate Change Impact on Agriculture

Agricultural systems exist at the nexus of human society and the physical environment, responding both to changes in demand as well as changes in the biophysical processes that govern crop growth. As such, agricultural systems were identified as a sector of interest in climate change research beginning two decades ago. The first global integrated assessment of the potential impact of climate change on world food supply was presented by Rosenzweig and Parry (1994). The authors relied on a network of crop modelers around the world to predict grain yield responses with locally calibrated models at 112 sites. Climate scenarios were generated for a doubling of atmospheric $CO_2$ for three GCMs. Site specific
yield changes in wheat, maize, soybean, and rice were used to estimate aggregate national yield changes for all crops based on similarity to modeled crop characteristics and growing conditions. The yield results were used as input into the Basic Linked System (BLS) model of agricultural trade. Yield changes were estimated with and without CO2 fertilization effects. The results showed that impact of changes in temperature and precipitation lower global yields in all crops, however when combined with the fertilization effect of doubled CO2, yields tended to be slightly negative for the majority of crops. The global yield figures mask a high degree of latitudinal variation, with higher latitude countries seeing lower impacts than tropical countries. Yield changes are dependent on the model scenario chosen, highlighting the sensitivity to assumptions of climate scenario. The yield models were then run allowing for systematic adaptation. Low cost methods of changes in planting date and fertilizer application were compared to higher investment strategies of irrigation infrastructure and changes in crop varieties. Low cost adaptation was found to have minimal effect on overall impacts, whereas higher cost adaptation strategies proved effective. Strikingly the disparities between developed and developing countries persist even under optimistic adaptation scenarios.

Continuing efforts have validated many of the key findings of Rosenzweig and Parry (1994) while building on advancements in both climate and crop models, as well considering the interactions between socioeconomic development and climate change. Parry et al. (1999, 2004a) offer an updated analysis using the many of the same methodologies as Rosenzweig, but expand the studies to utilize various developments in climate models and assumptions regarding CO2 fertilization effects. Fischer et al. (2005) focus on addressing the uncertainties inherent in scaling site level crop model data through an Agro Ecological Zone (AEZ) analysis, while Tubiello et al. (2007) focuses on comparing alternative scenarios of mitigation. Though these studies differ in the complexity of their methods they reach a consensus with respect to the regional distribution of impacts, the effects of socioeconomic assumptions, the benefits of adaptation, and the sensitivity to input model selection.
While each of these large scale studies has worked towards progressing the state of knowledge on the impact of climate change on agricultural yield, they all follow a very similar narrative that has remained nearly unchanged since the seminal work of Rosenzweig and Parry (1994). I present a schematic outline of the process in figure 1.2. To begin the modelers make some assumption about an emissions pathway. These emissions are an attempt to forecast the future outcomes of all of the collective activities of the global economy. It is easy to see how this exercise alone could yield an infinite possible futures, so researchers rely on a set of standardized scenarios that aim to classify pathways of global development (Nakicenovic et al., 2000). A small number of these scenarios (sometimes only one) are then used as the input for a model of the climate system. Each climate model is built with a given set of assumptions and parametric representations of complicated parts of the climate system. These models produce temperature and precipitation predictions which are then fed as the input to a crop model. Much like the climate model, the crop model is also built on a particular set of assumptions and parameterized relationships. The crop model estimates a change in yield for a given crop, at a given location or set of locations. This yield change is then put into a trade or integrated assessment model, with its own set of assumptions about the state of the world, in order to finally produce some economic outcome.

This process is built around constraining a very difficult problem in modeling: how do we deal with aspects of a complex system that we either do not fully understand, or lack the capacity to represent within the context of a model? By limiting inputs to single emissions scenarios, a few climate models, and one crop model, a researcher effectively attempts to bound the uncertainty of the problem. However it results in a state of cascading conditional dependence, where at each step of the process the current state is conditional on all the assumptions of the previous states. The only choice in interpreting these results becomes that of choosing between alternate futures. If the world develops along pathway X, then this could be the outcome, however if the world develops along pathway Y, this other outcome
may occur. This scenario based approach has the unintended consequence of obfuscating the uncertainty associated with the modeling process, and limiting the ability to accurately characterize the potential risk.

1.2 Limits to Characterizing Risk in Existing Crop Impact Studies

The risk of crop yield reductions from climate change is best understood through considering the distribution of historical yields for a given crop at a given location. This distribution is centered on the long-term average crop yield and spans a range of values owing to natural variability in the local climate. Using this distribution we can characterize the probability of obtaining a given crop yield, conditional on the current climate. If there is a systematic long-term change in climate, this distribution will shift, both in its mean and its standard deviation. This is shown by the 1 degree and 2 degree warming curves in figure 1.1. These new distributions now represent the probability of obtaining a given amount of yield conditional on a given amount of global mean temperature change. The risk from climate change relates directly to the change in probability.

This dissertation focuses on developing a modeling framework to predict the impacts of climate change on crop yield. In the first chapter I develop a methodology for characterizing the inter-model uncertainty in an ensemble of climate models. The approach extends the well known pattern scaling technique, which estimates the local change in a climate variable as a linear function of changes in global mean temperature. Using a multi-resolution Gaussian spatial process model I simulate a spatial process to represent the difference between the multi-model pattern and the individual models. In the second chapter I estimate the stable manifold response surfaces of various crops to changes in temperature and precipitation. I utilize the yield output of a process based crop model for 16 irrigated and non irrigated crops simulated at the county level in China. Using weather station data I fit a generalized additive model to growing season precipitation and growing degree days. This approach allows for non-linear relationships between yield and climate variables. Finally I
combine the pattern scaling approach in chapter 1 with the statistical fits from chapter 2 in order to estimate the impacts of climate change on crop yield in China.
Figure 1.1: A Conceptual Framework of Yield Loss Risk

- Current Climate
- 1 Degree Warming
- 2 Degrees Warming

Loss in Yield | Current Average Yield
--- | ---
Change in Yield
Figure 1.2: Historical Approach to Crop Impact Assessment

- Emissions Pathways → Scenarios → Climate Models
- Change in Yield
- Crop Model
- Changes in $T \& P$
- Integrated Assessment Model
- Economic Outcomes
Chapter 2

Spatial Probability Distributions of Global Climate Models from a Multi-Model Ensemble

2.1 Introduction

Global climate change has the potential to impact society and ecosystems in a number of ways (Parry et al., 2007b). Successfully adapting to these changes requires a comprehensive understanding of how the climate will change in response to human activity in the future. The primary tool for understanding the climate system are Global Circulation Models (GCMs)(Washington and Parkinson, 2005). However, the Earth’s climate system is complex and chaotic in nature, and any attempt to model is subject to a degree of uncertainty (Knutti et al., 2002). As a result different models can give contradictory results at a regional scale (Tubiello et al., 2007). Failing to account for this uncertainty in impact assessments can lead to underestimates of potential risks (Burke et al., 2011). Characterizing model uncertainty is therefore a crucial step in assessing the risks of climate change.

Climate model uncertainty arises from multiple sources (Knutti et al., 2008). Due in part to the imperfect knowledge of the response of the climate system to a given emissions scenario, many processes in the model must by simplified by parameterizing their effects. A classic example of this is cloud formation. Cloud formation occurs on a spatial scale that is much smaller than that of a climate model, therefore the process must be expressed in terms of other variables explicitly calculated from the model. Models vary in their choices of parameterization, and therefore vary in their output. Internal variability results from non-linear processes in the atmosphere and ocean, and accounts for a large degree of variation in model output (Deser et al., 2010). Uncertainty in future emissions results from imperfect knowledge of how future economic growth will affect the concentrations of greenhouse gasses
in the atmosphere.

There is rich body of literature focused on developing statistical methods for combining multiple climate models and quantifying their uncertainty (see Tebaldi and Knutti, 2007, for a thorough review). These methods vary in their complexity from simple comparisons of model standard deviation (Räisänen and Palmer, 2001; Giorgi, 2008) to more complex Bayesian models (Tebaldi et al., 2005; Smith et al., 2009; Tebaldi and Sanso, 2009). Most of these approaches treat these models as a distribution of possible future outcomes centered on the "true" future (eg Tebaldi et al., 2005), while others consider all models as statistically indistinguishable future outcomes (eg. Tebaldi and Sanso, 2009). Each of these approaches relies on a scenario approach to account for the uncertainty in future emissions, whereby a standard set of plausible future emissions pathways are considered as representing a range of future outcomes (Nakicenovic et al., 2000). However, because the scenarios have no associated likelihoods these approaches are all conditional on a the world following one distinct path of socio-economic growth (Schneider, 2001). It has been argued that uncertainties regarding emissions are not "intrinsic" akin to the uncertainties in model response (Knutti et al., 2008). Instead uncertainties represent the sum of many choices about economic development. Even within a single scenario models have been shown to have significant differences in radiative forcing (Forster and Taylor, 2006).

An alternative approach would be to condition uncertainty analysis on a change in global mean temperature rather than an emissions scenario. This has a few advantages over a scenario approach. The majority of impact assessment literature represent the effect of climate change on a vulnerable system in terms of a change in global mean temperature (Parry et al., 2007a). For policymakers who are interested in climate stabilization targets, using global mean temperature allows for the analysis of both transient change during the course of economic development, and locked in changes after stabilization (NRC, 2001). Furthermore, a method that relies only on changes in global mean temperature can be integrated with a simple energy balance model to explore changes across multiple develop-
ment pathways. One method of combining models across scenarios is the pattern scaling technique, which relies on a linear relationship between local changes in temperature and precipitation and changes in global mean temperature.

2.2 The Pattern Scaling Technique

The pattern scaling technique was first proposed two decades ago by Santer et al. (1990) as a methodology for translating the results of an equilibrium GCM experiments into other emissions scenarios, as well as a method for comparing the spatial patterns from different GCMs. Five climate models were run with equilibrium experiments at a doubling of CO$_2$. The spatial pattern of change between the equilibrium responses of doubling CO$_2$ and current CO$_2$ were normalized by the equilibrium global temperature change at double CO$_2$. Reasonable agreement between models was found for patterns of local temperature change, and thus the pattern scaling technique was born. The technique relies on the existence of a fixed geographic pattern of response for a climate variable that scales according to an increase in global mean temperature. It can be described analytically as follows: The anomaly of a climate variable $X$, at a particular spatial location $i$, in time period $t$, and forcing scenario $s$, is the product of a time invariant normalized spatial pattern $S$ and the corresponding change in global mean temperature $\delta T_{ts}$:

$$\Delta X_{its} = S_i \times \Delta T_{ts} + \epsilon_i \tag{2.1}$$

$S$ represents the field of normalized change in the climate variable of interest for a 1 degree change in global mean temperature. Pattern scaling thus provides a method for generating regional changes for time periods and scenarios not yet simulated by a GCM. Furthermore, as first suggested by Santer et al. (1990), it is possible to combine the pattern $S$ with a probability distribution for $\Delta T_{ts}$ generated from a simple climate model to rapidly generate fields of probabilistic climate change. Simple climate models (SCMs) have been
shown to emulate the global properties of more complex GCMs (Knutti et al., 2002). This is the approach adopted by the widely known MAGICC / SCENGEN software, which generates a probability distribution for changes in global mean temperature and relies on patterns derived from the CMIP3 database to produce detailed spatial output.

The pattern scaling technique relies heavily on the existence of a linear relationship between global mean temperature change and the local change in temperature or precipitation. A number of studies have addressed the validity of this assumption. Mitchell et al. (1999) provide the first rigorous analysis of the technique. The author analyzes how well a time-dependent response can be represented by a single pattern, and the assumption of linearity in the local response. The linearity assumption is found to hold best for local temperature, and finds that 99% of the variance in decadal temperature means is explained by pattern scaling. Patterns do not change significantly based on the rate of forcing, however the technique is shown to be less efficient in highly mitigated forcing scenarios. For precipitation the local change signal is found to be overshadowed by the effects of internal variability.

Huntingford (2000) examine the accuracy of scaling a SCM with a GCM derived pattern to derive additional scenarios. A land-ocean heat balance model is coupled with spatial patterns derived from a single model run under two separate transient forcing runs to generate an "analogue model". The analogue model is able to accurately predict responses across scenarios for temperature, with error being introduced when the pattern is extrapolated beyond the range of forcing at which it was initially calibrated. The technique is also tested for a variety of other surface variables, and is shown to perform weakest in rainfall rate.

Mitchell (2003) expands on their earlier analysis, this time addressing individual components of error that may be introduced through scaling. They revisit the crucial linearity assumption and identify slight non-linearities arising from the length of the warming period used to construct the patterns, the rate of warming, and the extent of stabilization. In contrast to Huntingford (2000) and Mitchell et al. (1999), sufficiently robust precipitation
patterns are calculated by extending the length of the averaging period to 30 years, and generating anomalies with respect to a control run rather than a climatological run. Errors are found to be the greatest when the pattern is calculated by subtracting two time periods, and the preferability of the regression approach is restated.

Giorgi (2005) examines the ability to scale between different scenarios at the regional level. The author compares the difference between the actual signal and the pattern scaled signal, and calls this quantity the nonlinear component of the signal. For temperature, the nonlinear fraction of the signal accounts for less than 25% of the regional signal. This fraction decreases in later decades, indicating that the strength of the linearity assumption increases as the strength of the signal to noise ratio of the warming increases. For precipitation, there is a great deal in variability across regions in the strength of the nonlinear signal owing to interdecadal variation that is not captured by the global temperature change series.

Estimating the response pattern $S$ can be approached a few different ways. The simplest approach relies on taking the difference between GCM output at two time periods, and dividing the result by the corresponding change in global mean temperature. This "time-slice" approach was the original approach used by Santer et al. (1990), and is also used for regional models in This approach requires only data from two time periods rather than requiring a full time series. Alternatively the pattern can be estimated using a least squares regression approach in which a time series of local anomalies is regressed on the corresponding time series of global mean temperature change (Mitchell et al., 1999; Mitchell, 2003; Huntingford, 2000). Mitchell (2003) demonstrates that the regression approach is more robust than a simple scaled difference approach as it places higher weight to time periods when global mean temperature is the highest, and therefore the forcing signal is highest with respect to the internal variability of the model. More recently Holden and Edwards (2010) employed an empirical orthogonal function approach aimed at maximizing the explained variance over the entire time period.
Beyond scaling to new emission scenario, the pattern scaling technique is also useful as a means of combining the results for multiple models and scenarios. For example, pattern scaling has long been used by the IPCC to show the average response across multiple models for a given scenario. Recently, Tebaldi and Arblaster (view) provided an assessment of the patterns of models in the CMIP3 and CMIP5 archive. By examining the standard deviation across models and scenarios separately they find that disagreement between models is the larger source of uncertainty. In essence, the pattern gives us the mean spatial response for a given amount of global warming around which all the models vary. From this viewpoint the task of characterizing the inter-model uncertainty becomes one of characterizing how much the models vary from scaled patterns at various degrees of warming. Rather than emulating the entire response of the model one could instead model the pattern scaling residuals as coming from a single data generating process, then create a synthetic GCM by adding the scaled pattern response to one realization of the residual process. By repeating this over and over a distribution of GCMs would be generated, and one could make inference from the distribution.

The key assumption here is that the residuals across models are statistically well-behaved. Based on the ordinary least squares regression assumptions, we are assuming that the residuals have an expected mean of zero, as well as constant variance. Non constant variance, or heteroskedasticity, will not effect the local parameter estimate of the pattern, but will effect inference on the pattern. This is an only an issue if the local pattern response is treated as a random variable to be sampled from, something that I do not consider in this work. However, it will present a challenge for parameterizing a single data generating process for the residuals, since the variance in those residuals will depend on the global mean temperature change. A simple visual way of testing this is to plot the residuals from pattern scaling against their associated changes in global mean temperature. Figures A.1 and A.3 show residuals of temperature from pattern scaling calculated for boreal winter at two spatial aggregations, regional and grid cell, respectively. Figures A.2 and A.4 show
the same for precipitation. For both variables the variance of the residuals, indicated by
the relative spread along the y-axis, remains fairly constant until about 2 degrees, at which
point it seems to increase. There are a number of possible reasons for this behavior, and it
is important to consider exactly what the residuals from pattern scaling represent.

The pattern itself represents the mean response across models of the climate system
to increasing green house gases (GHGs). It does not consider the impacts of other forcing
agents, or the idiosyncratic ways in which each model responds to GHG increases. In
particular the effects of short lived aerosol species, such as sulfates and black carbon, are
not included. The latter is what we are interested in capturing, as we want to estimate our
uncertainty in climate projections based on the spread of model responses. It has long been
understood that there is a linear additivity relationship between all forcing agents (Wigley,
1994), and, to the extent that the aerosol forcing is not correlated with the warming from
GHGs, the effects of these agents are present in the residuals. Because the residuals sample
across models and scenarios, and each scenario differs in its regional aerosol emissions, the
residuals are likely to show a high degree of variance. Additionally, the linear additivity
of forcings breaks apart for precipitation, leading to further nonlinear effects (Shiogama
et al., 2013). Based on these observations it is likely that the pattern scaling residuals may
depend on the total warming to some extent, and any method that aims to represent a data
generating process for the residuals must take this into consideration.

The principle motivation of this chapter is to answer the following question: How do
we move from discrete ensembles into probability distributions of risk? Here I propose
a methodology for characterizing the inter-model uncertainty in predictions of changes in
seasonal average temperature and precipitation. The technique relies on pattern scaling
across models and scenarios to determine the average multi-model spatial response to a one
degree change in global mean temperature. Residual fields for each model are calculated as
the difference between the model output and the multi-model pattern for a given amount
of warming. A multi-resolution Gaussian spatial process model is fit to the ensemble of
residuals using a restricted maximum likelihood estimation. The fitted model is then used to rapidly simulate correlated random spatial fields that represent a full distribution of residuals. These residuals are added to the mean pattern to create a probability distribution of spatial fields of temperature and precipitation, conditional on a given amount of global mean temperature change. The technique is performed at 2° and 3° global mean temperature change to examine both the possible effects of residual heteroskedacity on the parameters of the spatial process, as well as identifying the additional risk generated by warming past the oft quoted goal of 2° warming. The results are be used to assess the probability of grid point changes in temperature and precipitation. Risk maps of exceeding a given amount of local warming or precipitation change are generated for each season, as well as regional probability densities. Section 2.3 outlines the data preprocessing and pattern scaling approach. Section 2.3.4 focuses on the spatial process model used to represent the data generating process of the residuals. Results are given in section 4.3.

2.3 Methods

2.3.1 Data Preprocessing

Climate data output were obtained from the Third Coupled Model Intercomparison Project (CMIP3) from 17 different GCMs. Temperature and precipitation fields were obtained for the A1B, A2, and B1 scenarios from 1980 to 2099. Models were selected on the basis of availability of both temperature and precipitation for a given scenario and the presence of a 20th century control run. All available ensemble runs for each model were averaged to decadal monthly means (eg. the average temperature in January over a 10 year period) and interpolated to a common T42 grid. Decadal means are used to minimize the noise introduced by short-term variability in the climate system, such as El Nino / Southern Oscillation, and maximize the signal in the pattern scaling technique. The T42 grid represents the coarsest common spatial grid, and represents a reasonable trade off between
representing regional features while minimizing the computational burden.

Seasonal decadal averages are calculated for four seasons corresponding to boreal winter, spring, summer, and fall: December, January, February (DJF); March, April, May (MAM); June, July, August (JJA); and September, October, November (SON). Seasonal anomalies are then calculated at the grid cell level with respect to a baseline average climatology of 1980-2000. Temperature anomalies are given as changes in degrees Kelvin, whereas precipitation anomalies are calculated as a percentage change from the baseline average. Global mean temperature change is similarly calculated for each decade as an area weighted difference between the baseline climate and the decadal mean.

2.3.2 Calculating Patterns

To calculate the spatial patterns of change I regress the grid cell temperature and precipitation change on global temperature change according to the following formula:

$$\Delta X_{i,s,m,t} = \beta_{s,i} \Delta T_{G}^{G} + \varepsilon_{s,i,m,t}$$ (2.2)

Where $\Delta X_{i,s,m,t}$ is the change in the local variable of interest (either precipitation or temperature) at grid cell $i$, in season $s$, in decade $t$, for model-scenario combination $m$. The coefficient $\beta_{s,i}$ represents the time invariant geographic response of the local variable $X$ to a 1 degree Celsius change in global surface temperature $T_{global}$. $\Delta T_{G}^{G}$ represents the change in average area weighted global surface temperature. $\beta$ is obtained through an ordinary least squares regression with no intercept. I omit the intercept to ensure that at zero global warming we have zero local change, by default, such that:

$$\beta_{s,i} = \frac{\sum_{t=1}^{10} \sum_{m=1}^{46} (\Delta T_{G}^{G} \Delta X_{i,s,m,t})}{\sum_{t=1}^{10} \sum_{m=1}^{46} (\Delta T_{G}^{G})^2}$$ (2.3)

Under this approach I treat each model by scenario combination as an equally likely, independent outcome. Doing this allows for the estimate of the pattern $\beta$ to represent
the stable manifold climate response across all models and scenarios. All deviation from this response is captured in the residual $\varepsilon$, which accommodates the fact that pattern alone cannot represent the entire spatial response of a GCM owing to the effects of natural variability and the limitations of the technique discussed previously.

2.3.3 Calculating Residuals

Residuals are calculated by comparing the pattern scaled field to the actual modeled fields at two degrees global warming. For each model by scenario I identify the decade in which global mean temperature change equals or exceeds two degrees. The two degree threshold is chosen as a trade off between maximizing the strength of the pattern scaling signal with respect to natural variability, as well as maintaining a reasonable sample size. For each of these decades the corresponding fields of temperature and precipitation anomaly are extracted, and residuals are calculated as the difference between the anomaly fields and the pattern scaled by the corresponding change in global mean temperature such that:

$$
\varepsilon_{i,s,m} = \Delta X_{i,s,m} - \beta_{i,s} \Delta T_{s,m}^G
$$

Each model has some amount of internal variability that can be thought of as the natural variability of the climate system. Even at the decadal scale this variability presents a significant amount of noise compared to the pattern signal. The residuals calculated in Equation 2.4 incorporate both this internal variability and the systematic differences between models.

Variability within the climate models results from the interactions of components of the climate system. Each component reacts to changes in the others on varying time scales, resulting in a system that is constantly varying and never in equilibrium. Some of this variation occurs as a result of external forcing, e.g., changes in greenhouse gas concentrations, some of it occurs without changes in external forcing, e.g., El Nino - Southern Oscillation. In order to calculate the unforced variability I obtain model runs for each model with 20th
century forcings. These runs contain both forced and unforced variability.

To determine the internal variability within the models I start with the 20C3M scenario runs. These runs are forced by historical changes in green house gasses and aerosols from 1900-2000, and need to be detrended before the variability can be computed. To do this I fit a smooth curve to the data using a robust weighted local regression following Cleveland (1979). For each model \( m \), season \( s \), and grid cell \( i \) a polynomial function is fit at every time step \( t \) to the time series of temperature and precipitation. At each grid cell the function is fit using the values of neighboring points weighted by their distance from each point, such that:

\[
X_{i,s,m,t} = G_{i,s,m}(t) + \epsilon_{m,i,t}
\]  

(2.5)

\( G_{i,s,m}(t) \) is fitted using a weighted least squares procedure with weights determined using a tricubic weighting function. The time series of the residual \( \epsilon_{i,s,m,t} \) now represents the difference between temperature or precipitation at a given time, and a smoothed long run trend. Internal variability, \( \sigma_{m,i} \) is estimated as the sample standard deviation of \( \epsilon_{i,s,m,t} \) averaged across all models such that:

\[
\sigma_{m,i} = \frac{1}{M} \sqrt{\frac{1}{T} \sum_{t}^{T} (\epsilon_{m,i,t})}
\]  

(2.6)

where \( M \) represents the total number of models used and \( T \) represents the length of the time series.

The residuals are now divided by \( \sigma_{m,i} \) to emphasize the strength model specific departures from the pattern estimates compared to the internal variability,

\[
\hat{\epsilon}_{i,s,m} = \frac{\epsilon_{i,s}}{\sigma_{m,i}}
\]  

(2.7)

For \( \Delta T_{s,m}^G = 2^\circ \) this results in 29 fields of standardized temperature and precipitation
2.3.4 A Spatial Model for Residuals

Each field of residuals, $\hat{\epsilon}_{i,s,m}$, now represents a single model’s departure from the multi-model mean response of temperature and precipitation at 2 degrees global warming, scaled by a measure multi-model internal variability. Now the goal is to determine a statistical model that will explain the covariance in these fields. To do this I assume that each field represents a realization of an unknown spatial process. I assume that all of the fields are drawn from the same distribution, such that they share common parameters. By determining this parameters, conditional on the observed data, I can then simulate a distribution of spatial fields and make inference on them.

There is a rich field of statistical approaches for estimating models of spatial data (Diggle and Ribeiro, 2007). Most approaches rely on representing fields as realizations of Gaussian processes where $\{S(x) : x \in \mathbb{R}^2\}$ is a stochastic process where the joint distribution of $S = \{S(x_1), \ldots, S(x_n)\}$ is multivariate Gaussian. Such a function is completely specified by its mean function, $\mu(x) = E[S(x)]$, and covariance function, $\gamma(x, x') = \text{Cov}\{S(x), S(x')\}$. There are a range of standard covariance functions available, however they are limited in their application to large datasets due to the fact that inference on these functions requires taking the inverse of the covariance matrix. If the matrix is dense this becomes a computationally expensive procedure, where the time to compute a solution increases with the cube of the number of data points.

Because the motivation of this chapter is rapidly emulate GCMs with low computational overhead I instead chose a Gaussian process model designed to minimize this computational cost, given in Nychka et al. (2013). This approach is variation of Kriging using a set of fixed basis functions on a regular grid. The spatial correlation observed in the data is represented by weighting these basis functions using a set of coefficients that are modeled with a Gaussian Markov random field (GMRF). The GMRF is specified through a sparse
precision matrix resulting in a lower computational burden. Representing Gaussian random fields using a GMRF in combination with fixed basis functions has been shown to be advantageous over other approaches (Lindgren et al., 2011).

What follows is a description of the model and its assumptions as I have applied them. The full details of the model, including its performance compared to traditional spatial covariance models, can be found in Nychka et al. (2013). All model fitting and simulation are performed using the R package LatticeKrig.

I assume each field is an observation $y_i$ of an additive process with observations at unique two dimensional spatial locations $x_i$, for $1 \leq i \leq n$ according to:

$$y_i = g(x_i) + \epsilon_i \quad (2.8)$$

where $g$ is an unknown, smooth realization of a gaussian process, such that for any subset of the field the distribution is multivariate normal. The $\epsilon_i$'s represent random errors with mean zero. Here the spatial locations $x_i$ correspond latitude and longitude points on the T42 grid. In order to further diminish the computational burden I restrict the spatial domain to all points between 60° North and 60° South. This reduces the number of points in the domain by 32% while still maintaining coverage over the majority of inhabited land surfaces. The goal is to estimate $g(x_i)$ in equation 2.8.

$g$ is a representation of a spatial process with the form:

$$g(x) = \sum_{j=1}^{m} c_j \phi_j(x) \quad (2.9)$$

where $\phi_j$, for $1 \leq i \leq m$, represents a sequence of fixed basis functions. In other words, the smooth function $g(x)$ is made up of $m$ additive functions, each defined at a given location, or set of locations. These functions act as the building blocks for $g(x)$. Each of the functions is identical, however their contribution is scaled by coefficient $c_j$.

The default basis function assumption for LatticeKrig is to use a Wendland covariance
function of the form:

\[
\phi(d) = \begin{cases} 
(1 - d)^6(35d^2 + 18d + 3)/3 & \text{for } 0 \leq d \leq 1 \\
0 & \text{otherwise.}
\end{cases}
\]

where \(d\) is the distance between spatial locations. In this case \(d\) represents the space between grid cells, and each \(\phi(d)\) is scaled to be zero for distances \(d > 1\). The basis function coefficients, \(c_j\), are distributed as a multivariate normal and follow a GMRF with a mean of zero and a covariance matrix \(\rho P\), such that:

\[
c \sim \text{MVN}(0, \rho P) \tag{2.10}
\]

This implies the following covariance function:

\[
E[g(x), g(x')] = \Sigma_{j,k} \phi_j(x)\rho_{P,j,k} \phi_j(x') \tag{2.11}
\]

The coefficients, \(c\), are constructed as a Markov random field, following a spatial autoregression formulation such that:

\[
(4 + \kappa^2)c_j - \sum_{l \in N} c_l = e_j \tag{2.12}
\]

where \(\{e_j\}\) are uncorrelated \(N(0, 1)\) and \(N\) represent the 4 nearest neighbors. Equation 2.12 can be equivalently written in terms of an autoregressive matrix \(H\), such that when it premultiplies a matrix of correlated basis functions the result is an uncorrelated field of random noise:

\[
Hc = e \tag{2.13}
\]

This formulation allows for the inverse of the covariance matrix of \(c\), to be sparse, with
\( P = (H^T H)^{-1} \). This is the key aspect of the model which allows for the rapid computation of large spatial datasets.

Equations 2.9 through 2.13 can be used to fully describe a spatial process on a given grid. However, an additional strength in the method given in Nychka et al. (2013) is that 2.9 can be expressed as the sum of spatial processes on multiple grids. At each successive grid the spacing between the grid points is halved, and a separate GMRF is fit to the coefficients at each level. Each of these layers is taken to be independent of each other with a different correlation scale, \( \kappa^2 \), and marginal variance \( \rho_{\alpha_l} \). The full spatial model can be written as a weighted sum of \( L \) independent layers such that:

\[
g(x) = \alpha_1 \sum_{j=1}^{m(1)} c_1^j \phi_{j,1}^*(x) + \alpha_2 \sum_{j=1}^{m(2)} c_2^j \phi_{j,2}^*(x) + \ldots + \alpha_L \sum_{j=1}^{m(L)} c_L^j \phi_{j,L}^*(x) \quad (2.14)
\]

The coefficients \( \alpha_1, \alpha_2, \ldots, \alpha_L \) represent positive weights. In the case that \( L = 1 \) the basis functions \( \phi_j \) have an overlap equal to 2.5 times the distance between them.

Following this spatial model the residual fields of temperature and precipitation given in Equation 2.7 were fit using the \texttt{LatticeKrig} package in R using restricted maximum likelihood. The derivation of the likelihoods and simulation algorithms are given in Nychka et al. (2013). After many trials I found that for temperature the model fit best using a single level basis function grid of 32 by 32, for a total of 1,024 basis functions. For precipitation, which exhibits finer scale variation in the residual fields, I chose a two-level fitting procedure with the first grid fit at 32 by 32 and the second fit at 64 x 64 for a total of 5,120 basis functions. The results of the simulations are given in section 4.3.

\section*{2.4 Results}

Detailed explanations of the results as well as a full suite of diagnostic plots can be found in appendix A.
2.4.1 Global Patterns of Temperature and Precipitation

Multi-model average patterns of seasonal temperature change are given in figure 2.1. These maps show the multi-model average local response in surface air temperature to a 1 degree change in global mean temperature with respect to the reference period of 1980-2000 for each season. For temperature there is a distinct pattern of accelerated warming over land surfaces compared to the oceans. Another key feature is the amplified surface warming in the northern Arctic latitudes. The high degree of polar warming has a distinct seasonal attribute. It is most notable in the boreal winter panel, with some areas warming at nearly five times the global rate. During the summer months the amplification is smallest as the excess heat is taken up by the melting of sea ice and absorbed by the exposed ocean.

Similar averages are shown for precipitation in figure 2.2 in terms of percentage change from the 1980-2000 reference period. When interpreting these maps it is important to consider the high degree of inter-model uncertainty. In many areas models differ not only in the amplitude of change but also the sign of the change. This results in an average map that depicts a very smoothed response and is quite muted in terms of extremes. Most notably there is an overall tendency of models to show large increases in annual mean precipitation over the equatorial pacific ocean. This is consistent across seasons, however the intensity is slightly higher during the summer months. The mid to high latitudes see a slight degree of increase in precipitation while the sub-tropical regions see a more pronounced drying.

2.4.2 Global Risk of Temperature and Precipitation Change

Using the 10,000 simulated GCM runs I calculated the probability of a grid cell experiencing more than a 2°, 3°, 4°, or 5° Celsius increase in local average temperature during each season for global temperature change of 2° and 3°. A similar operation is performed for precipitation, looking at the probabilities of a given grid cell experiencing a 10% or 25% increase or decrease in seasonal precipitation. For temperature, the local risks at each level of warming are notably higher over land surfaces. This is expected, given the difference
in thermal properties between land and sea. In general risk of warming increases in the northern latitudes. Moving from 2° warming to 3° warming there is a notable risk increase at every threshold, in particular over land areas in the Southern Hemisphere.

During the boreal winter the highest risk areas are located in the northern hemisphere in the high latitudes. The area surrounding Hudson Bay consistently shows high levels of risk, with a large chance of exceeding the level of global warming locally. Portions of Western Europe show a noticeably lower level of risk than the rest of Europe. Moving into spring the areas of high risk shift southward, and risk increases in Western Europe. During the summer months we no longer see the anomalous hot spot over the Hudson Bay. Risk shifts towards the mid latitudes, with sections of the United States, Western and Southern Europe, and Central Asia all showing a high degree of risk of exceeding 5° under the 3° global warming scenario. The risk levels in the United States are at their highest levels during the summer compared to each other season. During the autumn we see a very high level of risk located in South America. A key feature of the autumn fields is the absence of the risk hot spot over the Hudson Bay. This is notable given its intense presence during the winter months, indicating that there is a high degree of seasonality in the risk patterns between autumn and winter.

Precipitation risk maps are presented in Figures 2.11 through 2.18. Precipitation risk is treated differently than temperature. Given the tendency for some models to predict increases and others to predict decreases in the same area, the resultant risk calculations show values for both increased as well as decreased precipitation. The result in some regions are a nearly equal risk of increase and decrease in average precipitation. Unlike the temperature fields, precipitation risk does not follow an obvious land/ocean trend, rather it presents itself as broad features across latitudinal bands. In general there is a tendency towards higher risk of decreased seasonal average precipitation across the subtropics into the lower edges of mid latitudes. Over the tropics and higher latitudes there is a strong tendency towards increased precipitation, with a large swath of high risk over the equatorial
Pacific. Moving from 2° and 3° degree warming results in a slight increase in the intensity of both the risk of increased and decreased precipitation. This pattern is most notable in the strong increase of risk associated with increased precipitation through the high latitudes.

From the seasonal perspective there is a general agreement in the patterns of risk across seasons, with some variation in the intensity of the risk. During the winter there is a high degree of risk of increased precipitation focused on the northern high latitudes. A notable feature is the high risk of increased precipitation that stretches through Russia down to the majority of the northern portion of China. Similarly there is a strong tendency towards mid-latitude drying. Moving into Spring the mid latitude drying risk remains fairly strong and the risk of northern latitude increases decreases in intensity but retains the geographic signature seen in the winter months. During the summer there is a noticeable shift in drying risk towards the higher latitudes. This is especially prevalent for the whole of Europe, while to the east there still remains a chance of increased precipitation. During the Autumn months the general patterns resemble the summer however there’s less of a risk of drying over the entirety of Europe with more of the risk focused towards the southern edge of the continent.

There is an inherent difficulty in validating the fit of the spatial model, owing to a number of factors. The first is the difficulty in comparing two distributions when one of the distributions has many orders of magnitude more members than the other. The other is considering the issue of independence, or a lack thereof, between the models included in the ensemble. To address these fitting questions I employed two approaches. The first is visual, in plotting the distributions of the ensembles against histograms of the models. The second is comparing the probability mass in various portions of the distributions. A full treatment and discussion of these results is given in A. In comparing the probability density mass I find an overall tendency for the synthetic distributions to be much wider than the underlying empirical distributions. In some regions this effect is less prominent, however overall the spatial model predicts more extreme outcomes in both directions.
2.4.3 Discussion

The aim of this methodology is to enable a risk based approach to climate impact assessment by introducing probabilities at the level of the climate model. To accomplish this requires sampling across both models and scenarios. In doing so there is an implicit assumption that all models retain the same skill in forecasting future climate. In simpler terms I choose not to weight the models. Additionally, at the core of this methodology is an assumption that each of the models included in the analysis is statistically indistinguishable, rather than considering the models as independent draws that are centered on the truth. This paradigm is supported by the fact that many of the climate models in the CMIP3 database have been shown to have significant spatial correlations in their error biases Jun et al. (2008), and therefore the strength of the climate signal does not improve with additional models Knutti et al. (2010). This is especially prevalent when single modeling groups produce multiple models that share structural elements and parameter choices. Recent analysis has suggested that both paradigms are valid, with model simulations of current climate falling into the truth-centered description, and future projections being indistinguishable Sanderson and Knutti (2012). Because it is impossible to validate the long term performance of a climate model the philosophical question of how to approach modeling uncertainty will persist, with support for both paradigms.

Many of the key assumptions of this work violate known physical processes, namely the assumption of independence in temperature and precipitation and independence between seasons. These choices were made to enable a computationally tractable result, and present an opportunity for future research. Much more work could be done in addressing the issue of model fit. Further improvements could be made to the pattern scaling technique. In particular controlling for aerosol response could provide more detail on the spatial patterns of response, as well as isolate the true mean response to the monotonic increase in greenhouse gases separate from the short lived responses to aerosol forcing. A key question that remains is whether the distribution of synthetic values should in some way be bounded by
the distribution of empirical values. This is challenging not only for the methodological issues previously presented, but also for the implications for impact assessment, where extreme values often drive outcomes (e.g., the nonlinear effect of exposure to high temperatures on corn yields reported by Schlenker and Roberts (2009)).

2.5 Conclusions

In this chapter I have developed an approach to generating spatially coherent probability distributions for changes in seasonal temperature and precipitation, conditional on a 2° or 3° change in global mean temperature. In doing so I am able to move from discrete ensembles of scenario dependent model outcome towards probability distributions of the stable manifold response to changes in global mean temperature across models and scenarios. First, I estimated the average spatial patterns of temperature and precipitation change for 17 GCMs. Next I used a spatial Gaussian process model to characterize the differences between the average spatial pattern and the individual model results, and to produce risk heat maps depicting the probability of exceeding a given threshold of change. This procedure was completed for all available GCM outputs in the CMIP3 database for all models exceeding 2° and 3° global mean temperature change. Separate spatial models were fit for each level of global mean temperature change to account for the possibility of heterogeneity in the pattern scaling residuals. In general the synthetic distributions of change are wider than the empirical distributions given by the GCMs themselves.

This approach provides many benefits over alternative strategies. Pattern scaling provides a computationally efficient technique to describe both the average response of local temperature and precipitation across both models and scenarios. This allows for the combination of multiple models, while also allowing one to present results conditional on a change in global mean temperature rather than an assumed socioeconomic pathway. As a result, this methodology could be combined with a simple climate model to explore uncertainties for any emissions pathway of interest. The spatial model used also presents significant com-
putation benefits, allowing me to simulate 10,000 synthetic GCM runs in roughly two and a half hours on a laptop computer. These benefits result in a technique that is attractive for including the effects of climate model uncertainty into impact and integrated assessment models.

This chapter provides a basic framework for further investigation and improvement. The technique should ideally be assessed for the most current generation of GCMs in the CMIP5 database. This would also allow for examining the behavior across a wider degree of global mean temperature changes, and results could be given for a broader range of changes in global mean temperature. In particular the dependance of the spatial process marginal and error variance on global mean temperature should be further assessed. This technique could be further extended by considering both the correlation between temperature and precipitation, as well as the correlations between seasons. Further development could also include the regional effects of aerosol emissions, which would provide an additional linkage to existing integrated assessment models which produce regional estimates of aerosol forcing.
Figure 2.1: Patterns of Seasonal Temperature Change
Figure 2.2: Patterns of Seasonal Precipitation Change
Figure 2.3: Temperature Risk Map at 2 degrees Global Warming - December, January, February
Figure 2.4: Temperature Risk Map at 2 degrees Global Warming - March, April, May
Figure 2.5: Temperature Risk Map at 2 degrees Global Warming - June, July, August
Figure 2.6: Temperature Risk Map at 2 degrees Global Warming - September, October, November
Figure 2.7: Temperature Risk Map at 3 degrees Global Warming - December, January, February
Figure 2.8: Temperature Risk Map at 3 degrees Global Warming - March, April, May
Figure 2.9: Temperature Risk Map at 3 degrees Global Warming - June, July, August
Figure 2.10: Temperature Risk Map at 3 degrees Global Warming - September, October, November
Figure 2.11: Precipitation Risk Map at 2 degrees Global Warming - December, January, February
Figure 2.12: Precipitation Risk Map at 2 degrees Global Warming - March, April, May
Figure 2.13: Precipitation Risk Map at 2 degrees Global Warming - June, July, August
Figure 2.14: Precipitation Risk Map at 2 degrees Global Warming - September, October, November
Figure 2.15: Precipitation Risk Map at 3 degrees Global Warming - December, January, February
Figure 2.16: Precipitation Risk Map at 3 degrees Global Warming - March, April, May
Figure 2.17: Precipitation Risk Map at 3 degrees Global Warming - June, July, August
Figure 2.18: Precipitation Risk Map at 3 degrees Global Warming - September, October, November
Chapter 3

Crop Yield Response to Temperature and Precipitation Change in China

3.1 Introduction

Making inferences about the potential impact of climate change on crop yields necessitates an understanding of how crop growth is impacted by changes in climatic variables. This requires a representative model that connects changes in variables such as temperature and precipitation to changes in the yield of a given crop at a given location. Developing such a model is a complex task, as crop growth is governed by the interaction of biophysical variables, such as temperature and precipitation, and management techniques, such as fertilizer application and irrigation (Lobell and Burke, 2010a). Furthermore, yield responses to these variables may differ across geographic space depending on local factors such as soil quality.

Traditionally, large scale assessments of the effect of climate on crop yields have relied on process based physiological models to estimate these interactions (Parry et al., 1999, 2004b). While process based models represent the best available understanding of how crops respond to environmental factors, their accuracy is dependent on a large amount of input data. This data may not be available for a given area of interest. In particular there is often a scarcity of relevant data in developing countries, where agricultural production represents a large share of the population’s total income. Understanding crop and climate relationships in these countries is key to reducing vulnerability to climate change.

An alternative approach is to develop a statistical model to estimate the relationship between historical yield and climate variables. Under this approach inference is drawn from the statistical relationships between historical yield and climate observations. These
relationships are then used to project future yields using the output of climate models. These statistical models require fewer data inputs than physiological models and therefore are well suited to situations where there is a scarcity of data. Additionally the spatial scale of statistical models is generally larger and well suited for use in assessments at the regional or global scale.

The objective of this chapter is to estimate reduced-form response surfaces of crop productivity changes as a result of climatic shifts in a data poor environment. This is accomplished through a "perfect model" approach (Lobell and Burke, 2010b). Under this approach the time series output from a process based model acts as a proxy for actual crop yield. A statistical model is then fit to the simulated data using historical temperature and precipitation records. In order to capture the potentially non-linear relationship between temperature, precipitation and yield I specify functional forms using a general additive model (GAM). This approach is an extension to the spline approach presented in Schlenker and Roberts (2009), and is well suited for capturing the adverse effects of a high degree of heat exposure.

3.1.1 Background

Parry et al. (1999) present the first global integrated assessment of the potential impact of climate change on global food supply. Climate scenarios for a doubling of atmospheric CO$_2$ levels were generated for three GCMs and used to predict grain yield responses using crop models that were validated at 112 sites. Site specific yield changes in wheat, maize, soybean, and rice were used to estimate aggregate national yield changes for all crops based on similarity to modeled crop characteristics and growing conditions. The yield results were used as input into the Basic Linked System (BLS) model of agricultural trade. Yield changes were estimated with and without CO$_2$ fertilization effects. The results showed that impact of changes in temperature and precipitation lower global yields in all crops, however when combined with the fertilization effect of doubled CO$_2$, yields tended to be
slightly negative for the majority of crops. The global yield figures mask a high degree of latitudinal variation, with higher latitude countries seeing lower impacts than tropical countries. Yield changes are dependent on the model scenario chosen, highlighting the sensitivity to assumptions of climate scenario.

The yield models were then run allowing for systematic adaptation. Low cost methods of changes in planting date and fertilizer application were compared to higher investment strategies of irrigation infrastructure and changes in crop varieties. Low cost adaptation was found to have minimal effect on overall impacts, whereas higher cost adaptation strategies proved effective. Strikingly the disparities between developed and developing countries persist even under optimistic adaptation scenarios.

Continuing efforts have validated many of these key findings while building on advancements in both climate and crop models and beginning to consider the interactions between socioeconomic development and climate change Parry et al. (1999, 2004b) offer an updated analysis using the many of the same methodologies but including first transient runs of climate change and assumptions of future economic pathways. Fischer et al. (2005) focus on addressing the uncertainties resulting from scaling site level crop model responses to national level using data through an Agro-Ecological Zone analysis. Tubiello and Fischer (2007) focuses on comparing alternative scenarios of mitigation. Though these studies differ in the complexity of their methods they reach a consensus with respect to the regional distribution of impacts, the effects of socioeconomic assumptions, the benefits of adaptation, and the sensitivity to input model selection.

Across these models there is a clear consensus among a few key points. The first is that impacts are likely higher in developing nations in tropical climates than in developed countries in the mid-latitudes, as tropical countries are generally already in warm climates and a small amount of warming can push them out of optimal growing conditions. At the regional scale there can be a high degree of variation in impact, and this variation is highly dependent on the modeling assumptions that are made. Finally, while adaptation
measures can provide some relief, the most effective methods are likely to be expensive and potentially inaccessible in the developing world where impacts are the highest.

More recently the focus has shifted towards statistical methods for predicting crop yield utilizing large datasets of aggregate yieldLobell and Field (2007); Lobell and Burke (2010b); Tebaldi and Lobell (2008). Statistical models utilize historical data on crop yields and weather to solve simple regression equations. Statistical models are particularly well-suited for simulations where there is insufficient data to calibrate a process based model. This is often the case in small or developing countries where climate impacts are likely to be the greatestFischer et al. (2005). These models fall into three categories: time series approaches that utilize data from one area over time; panel methods that estimate across spatial and temporal variations, and cross-sectional methods that analyze spatial variation.

(Lobell and Burke, 2009) provides an overview of statistical models of crop response as an alternative to process based approaches, and outlines many of the benefits and challenges. The choice of temporal and spatial resolution for panels and cross-sections, method of detrending time series, and specification of the function form of the regression all influence the estimated coefficients and their interpretation. While time series and cross-sectional analyses can provide useful information, for the purposes of a large spatial dataset a panel approach is preferred as it allows for the control of the effect of unobserved and omitted variables.

In an effort to explore the effects cascading uncertainties in crop modeling, a recent coordinated modeling effort has brought multiple crop and climate models together. This coordination, known as the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) aims to evaluate the magnitude, rate, and pattern of climate change impacts on agricultural productivity Rosenzweig et al. (2014). The approach’s objectives include establishing the range of uncertainties in climate change impacts which providing guidance for future modeling efforts. Seven global scale gridded climate models were run under a variety of emissions scenarios and compared to their own simulations of present day yields. Models
within the study show general agreement towards negative impacts to major crops particularly at higher levels of warming. Results for maize and wheat show increases in production in high latitude areas and decreases in low latitude areas. Rice and soybean show consistent gains in the mid to high latitude, but results are more mixed in their results. Importantly, when models do not consider nitrogen fertilization the impacts are found to be less severe. The authors make a strong point for continued work in this area. The work in ISI-MIP provides a strong foundation for the comparison of modeling techniques and the potential for cascading uncertainties. It also provides a wealth of information from which empirical models can be further developed. One particular benefit is the ability to simulate process models to extreme values of climate change. This can alleviate the concern in statistical modeling of introducing error when extrapolating far outside of the range of the initial dataset.

Despite the differences in data requirements, it should be noted that empirical estimates must be developed to agree with the underlying physical processes that dictate crop growth. As an example, Schlenker et al. (2006) simulate the impacts of climatic variables on farmland values using a hedonic equation for farmland value on non-irrigated farmland in the United States. The authors utilize transformed climatic variables suggested by agronomic literature, and report results that are highly non-linear and consistent with the agronomic literature. These results are robust across multiple specifications of functional form and multiple census years, suggesting that farm value will be impacted non-linearly by changes in future climate. Schlenker and Roberts (2009) provide a well developed starting point for developing empirical estimates of the impact of climate change on individual crops rather than an aggregate measure of farmland value. The authors develop a polynomial functional form that captures the nonlinear impacts of temperature and precipitation on county level crop yield in the United States. Controlling for precipitation, technological change, soil quality, and unobserved spatial fixed effects, the regression is able to capture a non-linear yield response to temperature. This non-linearity is robust across multiple specifications of
technology and time-effects, and also remains between both cross-sectional and time series specifications. The strength of an empirical approach is further examined by Lobell and Burke (2010b) to assess the ability of a statistical model to reproduce the results of a process based model of wheat yields in Africa. The results suggest that statistical models are well-suited in projecting future yield responses, with their usefulness increasing at broader spatial scales.

Although process based models are the dominate method for addressing climate impacts on agriculture, these results suggest that empirical estimates of yield response to changes in temperature and precipitation at the country level are robust. Furthermore, predictions of future impact are inherently limited by the spatial scale of the GCM simulations used. Given the large spatial scales of GCM output, and the increased accuracy of statistical models as spatial scale increases (Lobell and Burke, 2010b), it is appropriate to utilize an empirical approach when focusing on regional to global scale impacts.

The combination of increased future warming and the potential for highly nonlinear impacts to yields presents a clear threat to the future of agriculture. Quantifying this threat in terms of risk requires moving away from a discretized scenario approach. To do this we must understand the response of a given crop to changes in various meteorological conditions. However we are limited by the lack of availability of historical datasets at the subnational level. To overcome this barrier we can rely on historical datasets of meteorological variables to force crop models and produce a "synthetic" set of historical data to which we can then apply a statistical model. In the following section I extend the methodology of Lobell and Burke (2010b) to simulate yield from a suite of crops from a process model to create reduced form response surfaces for individual crops to changes in temperature and precipitation. I extend the approach of Schlenker and Roberts (2009), utilizing a generalized additive model approach which allows for a non-linear relationship between climate variables and crop yields.
3.2 Methodology

3.2.1 Crop Model Data

Crop yield data was simulated across 2191 counties in China for growing seasons between 1981 and 2000 using the DeNitrification-DeComposition (DNDC) agro-ecosystem model Li et al. (1992). DNDC is a process based model that tracks the transfer of carbon and nitrogen in cropping systems while simulating soil temperature and moisture, crop growth, and trace gas emissions. DNDC has been applied extensively to studies of global and regional scale agricultural assessments (Zhang et al., 2002; Wang et al., 2008). At each site, the DNDC model estimates crop yield, water use, and carbon and nitrogen transport by simulating how weather, soil, and human activities impact the environmental factors that determine growth, water demand, biomass allocation, and yield.

DNDC was run using daily inputs of temperature and precipitation from the Modern Era Retrospective Reanalysis for Research and Applications (MERRA) dataset (Rienecker et al., 2011). Yield for each county is calculated for one representative site. For each county polygon data was taken from the MERRA grid cell that was the closest to the county polygon center. Data on crop cultivation for each county was taken from Qiu et al. (2003). County level soil properties, including texture, bulk density, pH, and carbon content were generated through the digitization of the Chinese Third National Soil Survey maps Shi et al. (2004); Tang et al. (2006). For each crop, in each country, simulations were run with full irrigation and no irrigation conditions for 20 years. For irrigated conditions all moisture needs were met at every time step, whereas for non-irrigated all moisture was provided through precipitation. Crops follow a fixed planting and harvest schedule, with planting occurring on day 121 and harvest on day 288. To represent the general trend of fertilization the model is simulated with a 1.6% annual increase in fertilization levels, and a step decrease in manure application rates in 1990. The crop distribution represents conditions for 2000, with simulated crops de-trended to match fertilizer and manure application rates. As a
result the interannual variability results capture only weather-driven interannual variability.

### 3.2.2 Functional Form

For the full panel of all $c$ crops, $j$ counties, and $y$ years, I estimate the reduced-form response surface of crop productivity change with climatic shifts using a GAM approach, such that:

$$ g(\mu_{c,j,y}) = \omega_j + \nu_y + S^T_e(T^e_{j,y}) + S^T_l(T^l_{j,y}) + S^P_e(P^e_{j,y}) + S^P_l(P^l_{j,y}) + \epsilon_{c,j,y} \quad (3.1) $$

where:

$$ E(Z_{c,j,y}) = \mu_{c,j,y} \quad (3.2) $$

$Z_{c,j,y}$ represents the DNDC simulated annual yield for crop $c$, in county $j$, for year $y$. Equation 3.1 describes the relationship between the expected value of crop yield at a given location during a given growing season as the sum of a county and growing season specific indicator and several smooth functions. The $g(\cdot)$ function is a smooth monotonic gaussian link function relating the expected value of crop yield to the sum of a set of smooth functions.

$T^e_{j,y}$ and $T^l_{j,y}$ represent cumulative growing degree days in county $j$ during year $y$ for early and late half of the growing season, respectively. Similarly, $P^e_{j,y}$ and $P^l_{j,y}$ represent the cumulative precipitation. Crop yield in DNDC is simulated between May and October, therefore the early season values are cumulative over May, June and July, and the late season values are cumulative over August, September, and October.

The smooth functions $S_i(\cdot)$ in equation 3.1 represent the sum of a set of basis functions such that:

$$ S_i(X_i) = \sum_{n=1}^{N} \beta_n(X_i) \quad (3.3) $$

where the $\beta_n$ in 3.3 represent smooth polynomial basis functions. This approach is
similar to that of Schlenker and Roberts (2009), whereby we aim to utilize a flexible functional form in order to fully capture nonlinearities in the dataset. This flexibility is rooted in assuming that the response is an aggregation of many polynomials and the fact that I assign no a priori assumptions to functional form, rather let the data dictate the form.

3.2.3 Exposure Plots

For the rice, soybeans, rice, sorghum, millet and potato yield datasets I generate histograms of the baseline climate data as well as simulated early and late season growing degree days and cumulative precipitation at 2 and 3 degrees global warming. The baseline exposure histograms are generated using the data points used to estimate each of the GAM log-yield responses. Precipitation histograms are generated for each month in the early and late growing seasons according to the method outlined in Chapter 2.

To calculate the GDD histograms I begin by generating temperature distributions for each month in the early and late growing seasons following the method outlined in Chapter 2. For each month, GDD are calculated following Thevenard (2011). GDD are defined as the sum of the differences between daily average temperature and a give base temperature. The cumulative value over a month is give as:

\[
GDD_b = \sum_{i=1}^{N} (T_i - T_b)^+ \]

where \( N \) is the number of days in the month, \( T_b \) indicates the base temperature, \( T_i \) indicates the average daily temperature, and the + superscript indicates that only positive values are included in the calculation. Direct calculation of equation 3.4 requires knowledge of the distribution of daily temperatures within a given month, whereas the pattern scaling technique yields a distribution of average monthly temperature, therefore I have no information about average daily temperature. Schoenau and Kehrig (1990) provide a simple method from calculating degree-days under the assumption that daily main temperatures
are distributed around the monthly mean, such that:

\[ GDD_b = N \cdot s_d[Z_b \cdot F(Z_b) + f(Z_b)] \] (3.5)

where:

\[ Z_b = \frac{T_m - T_b}{s_d} \] (3.6)

\( Z_b \) is the difference between the average monthly temperature \( T_m \) – \( T_b \) normalized by the standard deviation of the daily average temperature, \( s_d \). The function \( f \) represents a Gaussian probability density function, with mean 0 and standard deviation 1. The function \( F \) is the Gaussian cumulative density function, such that:

\[ f(Z) = \frac{1}{\sqrt{2\pi}} \cdot e^{-Z^2/2} \] (3.7)

\[ F(Z) = \int_{-\infty}^{Z} f(z) \cdot dz \] (3.8)

Again since I am dealing with monthly outputs I have no information regarding the standard deviation of daily temperature, \( s_d \). Thevenard (2011) provides a method for estimating \( s_d \):

\[ s_d = 3.228 - 0.0796 \cdot T_m + 0.1733 \cdot \sigma_{yr} \] (3.9)

Equation 3.9 relates the standard deviation of daily temperature to the standard deviation of the monthly average ambient temperature from the annual average ambient temperature, such that:

\[ \sigma_{yr} = \sqrt{\frac{\sum_{m=1}^{12}(T_m - T_{yr})^2}{12}} \] (3.10)
The monthly standard deviation was calculated using data provided by Matsuura and Willmott (2012), which provide monthly gridded average surface temperature interpolated to a 0.5 degree grid. Growing degree days were calculated for the early (May-July) and late (Aug-Oct) season following this approach for current average temperatures and pattern scaled temperatures at 2 and 3 degrees global mean temperature change, respectively.

Once the future distributions of GDD and precipitation were calculated they were then aggregated over the grid cells in which each crop is grown. Cropped grid cells were determined using the MIRCA2000 dataset of monthly irrigated and rainfed crop areas (Portmann et al., 2010).

3.3 Results

For each of the crops the log-yield response surfaces were plotted to assess the impact of early and late season GDD and precipitation on the yield response. A full description of these results, and accompanying figures, can be found in Appendix B. In this section I will focus on the general trends in the responses. Response surfaces for both irrigated and non irrigated corn are included in this section as representative samples of the entire suite of crops.

For non-irrigated crops the largest variability in yield response appears to come from exposure to early season GDD. There is a general trend across all crops for yield to rapidly increase with exposure to GDD, level off at some optimum value, and then decline thereafter. In general crops reach an optimum level of exposure at approximately 500 to 600 GDD. There is a higher degree of variability between crops in when the response begins to decline. For corn, the response remains fairly stable across a broad range of exposures before dropping gradually. Soybeans on the other hand enjoy an extremely narrow window of optimum exposure and then rapidly drop. Only rice, a paddy crop, shows no sensitivity to high levels of early season heat exposure. During the second half of the growing season there is less variability in the response to heat. Generally yields increase somewhat monotonically
and level off, showing little to no sensitivity to high levels of exposure. The exception to this rule is millet, beans, and oats, which show slight declines at the highest levels of exposure.

For precipitation the first order response is fairly homogenous across crops during both seasons. In the early season there’s an immediate increase followed by either a level response or a slight increase. There is no determent to exceeding a given level of precipitation, however low levels of precipitation during the early season will cause a reduction in yields. For the late season most crops remain almost entirely insensitive to precipitation, suggesting that the majority of beneficial precipitation effects occur during the early half of the season.

Irrigated crops show a much different response to early season GDD. While the initial increase and leveling of response is seen, the decline at high levels of exposure is much less than in the non-irrigated crops. Notably there is much more similarity between the early and late season responses in the irrigated crops compared to the non-irrigated crops. As would be expected the effects of both early and late season precipitation are trivial.

At 2 and 3 degrees warming the temperature distributions are much wider in both directions, shifting more towards the extremes when compared to the baseline. The distributions are also generally shifted towards higher values. For precipitation the effect is similar though much less noticeable, especially when comparing the 2 and 3 degree distributions, which look very similar. How these shifting distributions interact with the yield response curves will dictate the risk of impact to yield. These shifts depend crucially on where a crop, at a given location, is on the baseline distribution, compared to where it is on the distribution at 2 or 3 degrees warming. To explore this effect I calculate the conditional yield at each quantile of the distribution for each variable, while holding the rest of the input values fixed at their mean value.

Tables 3.1 through 3.12 show the conditional effect on the change log yield values along the quantiles of the early and late season GDD and precipitation distributions at 2 and 3 degrees global mean temperature change. Generally the impacts are higher at 3 degrees warming than 2 for most quantiles of GDD. For precipitation there’s almost no difference
between the two levels of warming.

3.4 Discussion

These results suggest that non-irrigated crops in DNDC are most sensitive to high levels of heat accumulation in the early part of the growing season. Precipitation has less of an impact on yield, however low levels of precipitation will lower yields. Perfect irrigation can be beneficial in mitigating this early season sensitivity, but cannot completely eliminate it.

The yield response surfaces here do not show the same level of nonlinearity at high heat exposure as was seen in Schlenker and Roberts (2009) (S+R). When comparing these results it is important consider the data inputs to both studies. For S+R the input meteorological dataset consists of county level daily min and max observations. From these values the authors are able to calculate heat exposure with a fine degree of granularity. In this study I have relied on translating decadal average temperature and precipitation from a climate model into seasonal sums. In doing so, I am forced to estimate the heat accumulation using an empirical relationship calculated using average monthly temperature and average monthly standard deviation. This method is not well suited for capturing extremes in growing degree days. Additionally, S+R rely on historical yield values rather than model simulation. While DNDC has been tuned to match historic yields, it may not inherently capture the same non-linear relationship between temperature and yields.

It is important to recall that DNDC handles irrigated crops by assuming that all water demands are met during each step of the simulation. To that extent the irrigated results provide a means of assessing the feasibility of a perfect irrigation scheme. Another way of thinking of this is to consider the irrigated results to be answering the question of how much the addition of water can ameliorate the potential negative impacts of high heat. What we see is that across most crops irrigation is able to mitigate the majority of the decline in yields that would normally be seen under conditions of extreme early season heat. It is, however, a dangerous extrapolation to assume that this condition would hold true for levels
of heat higher than that experienced in during the baseline period. It could very well be that the level of heat needed to experience detrimental effects even with perfect irrigation was not experienced during the 20 year period for which the model was run.

The astute reader may question the function of running a crop model and then estimating a statistical response surface. The natural question that follows is why not just utilize the model that you start with? It is important to recall that the goal of this chapter is to produce a means of characterizing the response of crops to changes in meteorological variables, in support of a risk analysis. These response surfaces are designed to work in parallel with the distributions of climate fields produced in the previous chapter. Running a model 10,000 times is not computationally feasible, however simulating the statistical model is.

### 3.4.1 Conclusion

The GAM specification provides a flexible method for capturing nonlinear relationships between crop yield and temperature and precipitation. For non-irrigated varieties, the log yield response to early season growing degree days tends to increase quickly to an optimum, then slowly decrease. The highest levels of heat accumulation during the first half the growing season tend to have negative effects. During the second half of the growing season the optimum heat accumulation is generally lower than the first half, with less of a negative impact for higher level of heat accumulations. For precipitation its the first half of the season that has the largest impact on yield. Low levels of early season precipitation have large impacts on yield, however the highest levels generally are not detrimental. Generally late season precipitation has minimal effects on yield.

For irrigated varieties the yield response behaves much differently. Crop yield response reaches an optimum value and remains constant above it for both the early and late seasons, showing no negative affects to high levels of accumulated heat. In some crops, such as millet and sorghum, the non-irrigated late season optimum heat accumulation occurred at higher values than the irrigated.
The effects of climate change are likely to be heterogeneous across irrigated and non-irrigated crops. Yield of non-irrigated crops are generally most effected by heat accumulated during the first half of the growing seasons, increasing quickly with heat accumulation reaching an optimum range before decreasing at higher levels. This suggests that not only the overall level of warming will effect

A few crops have sample distributions that do not align with their optimum yield ranges. In these cases most of the sample points are distributed at higher levels of early season heat accumulation. This is particularly evident in corn, soybeans, and sorghum. Not only are these crops being grown under sub-optimal conditions, but given that they are already growing beyond their optimum range, they are far more susceptible to losses in a warming climate. Additionally these crops tend to be grown at higher levels of heat accumulation.

The input dataset of crop yields was estimated using a model specification that was tuned using confidential data on county-level yields in China. Each county is given a unique identifying ID but the location remains unknown. As a result I am unable to address any underlying spatial auto-correlation that is likely to exist between geographically congruent counties.

In this chapter I have presented a method for applying a generalized additive model to the output of a crop model in order to estimate the yield response to changes in growing degree days and precipitation. A This approach is able to capture the nonlinear relationships between the climate variables and crop yield over the early and late part of the season. Perhaps most importantly, is the potential for applying this approach to other input datasets. In particular, the global gridded datasets developed through ISI-MIP.

ISI-MIP provides global datasets of predicted yield from the combination of multiple climate models as well as multiple crop datasets. From the point of view of an applied statistician this represents a treasure trove of data, produced under a set of rigorous assumptions. The basic approach would draw from the methodology presented here. The entirety of the dataset would be utilized for a single regression response. For each crop
the data would be regressed against meteorological variables represented as smooth basis functions, while also controlling for the climate and crop model used for estimation.
Figure 3.1: Non-Irrigated Yield Response: Corn Early Growing Degree Days
Figure 3.2: Non-Irrigated Yield Response: Corn Late Growing Degree Days
Figure 3.3: Non-Irrigated Yield Response: Corn Early Precipitation
Figure 3.4: Non-Irrigated Yield Response: Corn Late Precipitation

Late Season Precipitation

Log Yield Response
Baseline
2 Degree
3 Degree

0 500 1000 1500
Figure 3.5: Irrigated Yield Response: Corn Early Growing Degree Days
Figure 3.6: Irrigated Yield Response: Corn Late Growing Degree Days
Figure 3.7: Irrigated Yield Response: Corn Early Precipitation
Figure 3.8: Irrigated Yield Response: Corn Late Precipitation
<table>
<thead>
<tr>
<th></th>
<th>2° Warming</th>
<th></th>
<th></th>
<th></th>
<th>3° Warming</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>100%</td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>100%</td>
</tr>
<tr>
<td>GDD Early</td>
<td>0.193</td>
<td>0.005</td>
<td>-0.202</td>
<td>-0.230</td>
<td>0.331</td>
<td>0.150</td>
<td>-0.050</td>
<td>-0.066</td>
</tr>
<tr>
<td>GDD Late</td>
<td>-0.051</td>
<td>-0.037</td>
<td>0.027</td>
<td>-0.232</td>
<td>-0.083</td>
<td>-0.065</td>
<td>0.001</td>
<td>-0.265</td>
</tr>
<tr>
<td>PCP Early</td>
<td>-0.626</td>
<td>-0.095</td>
<td>-0.013</td>
<td>-0.467</td>
<td>-0.637</td>
<td>-0.104</td>
<td>-0.019</td>
<td>-0.462</td>
</tr>
<tr>
<td>PCP Late</td>
<td>-0.005</td>
<td>-0.004</td>
<td>-0.020</td>
<td>0.200</td>
<td>-0.005</td>
<td>-0.004</td>
<td>-0.020</td>
<td>0.204</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>2° Warming</th>
<th></th>
<th></th>
<th></th>
<th>3° Warming</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>100%</td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>100%</td>
</tr>
<tr>
<td>GDD Early</td>
<td>0.413</td>
<td>-0.292</td>
<td>-0.496</td>
<td>-0.637</td>
<td>0.713</td>
<td>-0.018</td>
<td>-0.245</td>
<td>-0.338</td>
</tr>
<tr>
<td>GDD Late</td>
<td>-0.187</td>
<td>0.079</td>
<td>0.366</td>
<td>0.583</td>
<td>-0.311</td>
<td>-0.071</td>
<td>0.188</td>
<td>0.366</td>
</tr>
<tr>
<td>PCP Early</td>
<td>-0.599</td>
<td>-0.206</td>
<td>0.032</td>
<td>-0.235</td>
<td>-0.622</td>
<td>-0.230</td>
<td>0.010</td>
<td>-0.214</td>
</tr>
<tr>
<td>PCP Late</td>
<td>-0.009</td>
<td>-0.023</td>
<td>-0.001</td>
<td>0.310</td>
<td>-0.008</td>
<td>-0.023</td>
<td>-0.001</td>
<td>0.308</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>2° Warming</th>
<th></th>
<th></th>
<th></th>
<th>3° Warming</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>100%</td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>100%</td>
</tr>
<tr>
<td>GDD Early</td>
<td>0.004</td>
<td>0.006</td>
<td>-0.003</td>
<td>-0.064</td>
<td>-0.004</td>
<td>-0.001</td>
<td>-0.007</td>
<td>-0.041</td>
</tr>
<tr>
<td>GDD Late</td>
<td>0.038</td>
<td>0.014</td>
<td>-0.008</td>
<td>0.051</td>
<td>0.032</td>
<td>0.009</td>
<td>-0.015</td>
<td>0.020</td>
</tr>
<tr>
<td>PCP Early</td>
<td>0.004</td>
<td>0.009</td>
<td>0.003</td>
<td>-0.068</td>
<td>0.005</td>
<td>0.010</td>
<td>0.006</td>
<td>-0.064</td>
</tr>
<tr>
<td>PCP Late</td>
<td>0.002</td>
<td>-0.002</td>
<td>-0.003</td>
<td>-0.022</td>
<td>0.002</td>
<td>-0.002</td>
<td>-0.004</td>
<td>-0.024</td>
</tr>
</tbody>
</table>
### Table 3.4: Non-irrigated Millet Log Yield Response by Quantile

<table>
<thead>
<tr>
<th></th>
<th>2° Warming</th>
<th></th>
<th>3° Warming</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25% 50% 75% 100%</td>
<td></td>
<td>25% 50% 75% 100%</td>
<td></td>
</tr>
<tr>
<td>GDD Early</td>
<td>0.351 0.013 -0.246 -0.390</td>
<td></td>
<td>0.469 0.130 -0.120 -0.113</td>
<td></td>
</tr>
<tr>
<td>GDD Late</td>
<td>-0.149 -0.068 0.052 -0.089</td>
<td></td>
<td>-0.251 -0.190 -0.089 -0.177</td>
<td></td>
</tr>
<tr>
<td>PCP Early</td>
<td>-0.269 -0.103 0.002 -0.174</td>
<td></td>
<td>-0.271 -0.102 0.005 -0.166</td>
<td></td>
</tr>
<tr>
<td>PCP Late</td>
<td>-0.001 -0.005 0.004 0.084</td>
<td></td>
<td>-0.002 -0.005 0.004 0.079</td>
<td></td>
</tr>
</tbody>
</table>

### Table 3.5: Non-irrigated Sorghum Log Yield Response by Quantile

<table>
<thead>
<tr>
<th></th>
<th>2° Warming</th>
<th></th>
<th>3° Warming</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25% 50% 75% 100%</td>
<td></td>
<td>25% 50% 75% 100%</td>
<td></td>
</tr>
<tr>
<td>GDD Early</td>
<td>0.124 -0.236 -0.444 -1.101</td>
<td></td>
<td>0.343 -0.014 -0.223 -0.884</td>
<td></td>
</tr>
<tr>
<td>GDD Late</td>
<td>-0.037 0.055 0.211 0.023</td>
<td></td>
<td>-0.143 -0.068 0.073 -0.078</td>
<td></td>
</tr>
<tr>
<td>PCP Early</td>
<td>-0.400 -0.066 -0.070 -0.433</td>
<td></td>
<td>-0.405 -0.066 -0.066 -0.412</td>
<td></td>
</tr>
<tr>
<td>PCP Late</td>
<td>-0.008 -0.016 0.008 0.109</td>
<td></td>
<td>-0.007 -0.016 0.007 0.106</td>
<td></td>
</tr>
</tbody>
</table>

### Table 3.6: Non-irrigated Potato Log Yield Response by Quantile

<table>
<thead>
<tr>
<th></th>
<th>2° Warming</th>
<th></th>
<th>3° Warming</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25% 50% 75% 100%</td>
<td></td>
<td>25% 50% 75% 100%</td>
<td></td>
</tr>
<tr>
<td>GDD Early</td>
<td>0.480 -0.237 -0.400 0.129</td>
<td></td>
<td>0.763 0.028 -0.157 0.321</td>
<td></td>
</tr>
<tr>
<td>GDD Late</td>
<td>-0.430 0.017 0.545 0.698</td>
<td></td>
<td>-0.672 -0.239 0.267 0.446</td>
<td></td>
</tr>
<tr>
<td>PCP Early</td>
<td>-1.370 -0.487 0.356 -0.048</td>
<td></td>
<td>-1.419 -0.545 0.291 -0.113</td>
<td></td>
</tr>
<tr>
<td>PCP Late</td>
<td>-0.072 -0.026 0.005 0.367</td>
<td></td>
<td>-0.070 -0.026 0.004 0.375</td>
<td></td>
</tr>
</tbody>
</table>

### Table 3.7: Irrigated Corn Log Yield Response by Quantile

<table>
<thead>
<tr>
<th></th>
<th>2° Warming</th>
<th></th>
<th>3° Warming</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25% 50% 75% 100%</td>
<td></td>
<td>25% 50% 75% 100%</td>
<td></td>
</tr>
<tr>
<td>GDD Early</td>
<td>-0.142 -0.024 0.018 -0.016</td>
<td></td>
<td>-0.175 -0.050 0.0001 0.003</td>
<td></td>
</tr>
<tr>
<td>GDD Late</td>
<td>0.007 -0.008 -0.0003 -0.217</td>
<td></td>
<td>0.006 -0.008 -0.001 -0.207</td>
<td></td>
</tr>
<tr>
<td>PCP Early</td>
<td>0.013 0.005 -0.029 -0.329</td>
<td></td>
<td>0.014 0.007 -0.026 -0.323</td>
<td></td>
</tr>
<tr>
<td>PCP Late</td>
<td>0.004 0.002 0.001 0.015</td>
<td></td>
<td>0.004 0.002 0.001 0.015</td>
<td></td>
</tr>
<tr>
<td>Table 3.8: Irrigated Soybean Log Yield Response by Quantile</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>----------------------------------------------------------</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2° Warming</td>
<td>3° Warming</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>100%</td>
</tr>
<tr>
<td>GDD Early</td>
<td>-0.035</td>
<td>-0.006</td>
<td>0.007</td>
<td>-0.024</td>
</tr>
<tr>
<td>GDD Late</td>
<td>0.014</td>
<td>0.0004</td>
<td>0.001</td>
<td>0.042</td>
</tr>
<tr>
<td>PCP Early</td>
<td>-0.005</td>
<td>-0.0003</td>
<td>-0.006</td>
<td>-0.013</td>
</tr>
<tr>
<td>PCP Late</td>
<td>0.001</td>
<td>0.001</td>
<td>-0.0005</td>
<td>-0.003</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 3.9: Irrigated Rice Log Yield Response by Quantile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>GDD Early</td>
</tr>
<tr>
<td>GDD Late</td>
</tr>
<tr>
<td>PCP Early</td>
</tr>
<tr>
<td>PCP Late</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 3.10: Irrigated Millet Log Yield Response by Quantile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>GDD Early</td>
</tr>
<tr>
<td>GDD Late</td>
</tr>
<tr>
<td>PCP Early</td>
</tr>
<tr>
<td>PCP Late</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 3.11: Irrigated Sorghum Log Yield Response by Quantile</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>GDD Early</td>
</tr>
<tr>
<td>GDD Late</td>
</tr>
<tr>
<td>PCP Early</td>
</tr>
<tr>
<td>PCP Late</td>
</tr>
</tbody>
</table>
Table 3.12: Irrigated Potato Log Yield Response by Quantile

<table>
<thead>
<tr>
<th></th>
<th>2° Warming</th>
<th></th>
<th></th>
<th></th>
<th>3° Warming</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>100%</td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
<td>100%</td>
</tr>
<tr>
<td>GDD Early</td>
<td>-0.023</td>
<td>-0.017</td>
<td>-0.033</td>
<td>-0.168</td>
<td>-0.012</td>
<td>-0.001</td>
<td>-0.015</td>
<td>-0.155</td>
</tr>
<tr>
<td>GDD Late</td>
<td>0.002</td>
<td>-0.002</td>
<td>-0.004</td>
<td>0.063</td>
<td>0.006</td>
<td>0.007</td>
<td>0.006</td>
<td>0.059</td>
</tr>
<tr>
<td>PCP Early</td>
<td>0.005</td>
<td>0.001</td>
<td>-0.006</td>
<td>-0.202</td>
<td>0.005</td>
<td>0.001</td>
<td>-0.005</td>
<td>-0.201</td>
</tr>
<tr>
<td>PCP Late</td>
<td>0.0003</td>
<td>-0.001</td>
<td>0.001</td>
<td>-0.004</td>
<td>0.0004</td>
<td>-0.001</td>
<td>0.001</td>
<td>-0.002</td>
</tr>
</tbody>
</table>
Chapter 4

Calculating Yield Shocks to Chinese Agriculture using Pattern Scaling

4.1 Introduction

China is one of the leading producers of global agricultural products. Recent studies have suggested that climate change has already begun to impact agricultural yields. As population pressures increase identifying areas at the highest risk will become essential to developing successful adaptation strategies. Furthermore, China’s contribution to the global agriculture market suggests that any impacts to national level agricultural production may have effects on global commodity prices.

Previous studies of climate impact on agricultural productivity in China have had mixed results. However, Wang et al. (2014) point out that the majority of this variability is owing to the treatment of $CO_2$ fertilization in process-based crop models. For example, Chavas et al. (2009) force a process model with the output for a regional climate model and find negative impacts to rice, canola, corn, wheat, and potato without considering the potential $CO_2$ effects, however results become overwhelmingly positive when it is included. Tao et al. (2009) develop a super-ensemble probabilistic projection approach to address the relative uncertainty of emissions scenarios and biophysical impacts for maize production on the North China Plain and find reductions of upwards of 31% by the end of the century. Tao and Zhang (2012) relied on a similar super ensemble process based model approach to assess the effects of climate change on rice and found end of century impacts varying from as much as 39% reduction in yields to a 25% increase, with the difference owing mainly to the treatment of $CO_2$ fertilization effects. Wassmann et al. (2009a,b) review the effects of various climate change induced stressors on rice cultivation and conclude that current
summertime temperatures in China are already close to a critical limit for rice development.

Studies indicate that irrigated cultivars are also at risk, though the risk tends to be lower than that for non irrigated varieties. Tao and Zhang (2011) show that a temperature increase of 1 degree can lead to reduction in yield of up to 10.9%. Recently Tao et al. (2014) examined observations at 120 agricultural research stations over a 28 year period to determine the impacts of climate on wheat over the time period. The authors found that climate change had caused notable impacts on wheat growth and productivity, with increases seen in the north and decreases in the south. Most notably the authors note that these changes occurred during a period in which management and cultivars were shifted to accommodate and adapt to a changing climate.

In this chapter of my dissertation I address the following question: What cropping regions are likely to experience negative impacts from climate change. To accomplish this I combine a statistical model of crop yield for six primary crops generated in Chapter 2 with the pattern scaling output from an ensemble of climate models from Chapter 1 to develop country wide impact potentials for corn, soybean, rice, sorghum, millet and potatoes. I then rely on a dataset of cropped area to determine the loss for irrigated and non irrigated crops, before combining them to generate maps of total impact. Rather than assuming an uncertain socioeconomic pathway I condition these results only on changes in global mean temperature, using two and three degrees warming as benchmark values. In section 4.2 I detail the experimental approach and datasets used. In section 4.3 I discuss the findings for each crop, and discuss the results in section 4.3.3.

4.2 Methodology

4.2.1 Calculation of Growing Degree Days from Climate Model

In order to simulate the yield response models estimated in Chapter 2 it is necessary to generate current and future predictions of growing degree days and cumulative precipitation.
Current values of monthly temperature and precipitation were taken from the model ensemble monthly average from 1980-2000. Future values were generated following the regression pattern scaling approach outlined in Chapter 1. The monthly patterns for temperature represent the local change in temperature in each grid cell corresponding to a 1 degree change in global mean temperature from the model ensemble average of 1980-2000. The monthly patterns for precipitation represent the local percentage change in precipitation corresponding to a 1 degree change in global mean temperature for the same time period. Each of these patterns was then used to calculate monthly mean values for global mean temperature changes of 2 and 3 degrees. Growing degree days were calculated following the method outlined in the previous chapter.

4.2.2 Crop Specific Impacts

Crop specific impacts were calculated by fitting the generalized additive models outlined in chapter 2. The values of current and future growing degree days and precipitation were first interpolated to a common grid resolution of 2.5 degrees using a linear spline interpolation technique (Akima, 1978). Log yield predictions were made at each grid cell for current average conditions, 2 degree and 3 degree global mean temperature change conditions for irrigated and non-irrigated corn, soybeans, millet, sorghum, rice and potatoes.

For each individual crop type irrigated and and non irrigated impacts were first separately calculated. The results of the model fit are in units of log yield. Differencing the log yield results is the equivalent of the log of the ratio of the two. This value is then exponentiated to determine the ratio, or percentage change, of future yield at 2 and 3 degrees global mean temperature change, respectively.

Total potential impact for each of the crop types is calculated by weighting each crop by the planted acreage of irrigated and non-irrigated management. Acreage data was calculated from the MIRCA2000 dataset of monthly irrigated and rainfed crop areas (Portmann et al., 2010). For each of the crops the total acreage for each management regime was taken as
the sum of all sub crops in the dataset. Total crop impact is calculated as follows:

\[
\Delta Y^c_{x,y} = A^c_{i,x,y} \cdot \Delta Y^c_{i,x,y} + A^c_{n,x,y} \cdot \Delta Y^c_{n,x,y}
\]

(4.1)

\(\Delta Y^c_{x,y}\) is the total yield for crop \(c\) at grid cell \(x, y\). \(A^c_{i,x,y}\) and \(A^c_{n,x,y}\) is the total acreage for crop \(c\) at location \(x, y\) for irrigated \(i\) and non-irrigated \(n\) management, respectively.

Equation 4.1 is calculated at a half degree resolution corresponding to the MIRCA2000 dataset.

4.3 Results

4.3.1 Irrigated vs Non-irrigated Impacts

Crop specific results are given for each management regime in figures 4.1 through 4.12. For each of these figures impacts are shown over areas where crops are currently grown.

Log yield change for corn production at two degrees warming is given in figure 4.1 for non irrigated and irrigated management regimes. Nonirrigated log yield values are lowest along a corridor extending from the Yunnan province northeast through Beijing. Areas of high impact occur in southern Xinjiang province, northern Gansu and sections of inner Mongolia. Some areas of positive log yield change are seen around the norther border of Qinghai and Gansu provinces. Log yield change for irrigated management overall shows much less impact. Areas of decreased log yield are concentrated to the south western portion of the country, and are the highest in Guangdong and Fujian provinces. The north westerly tract of strong negatives impacts seen in the non irrigated map appears mostly positive. There is a general trend from negative to positive impacts moving from southeast to northwest, with positive impacts generally occurring at the mid-elevations in the center of the country.

Log yield change for corn production at three degrees warming in given in figure 4.2 for non irrigated and irrigated management regimes. Non irrigated low yield values show
similar patterns as the lower level of warming but with higher degrees of impact. The strong impact through the middle elevations following the transect from Yunnan to Beijing is still prevalent, with impacts nearly doubled in some areas. For irrigated management the patterns remain similar to the two degree warming case, however only the negative impacts along the south eastern edge of the country are significantly increased. The positive impacts remain similar to those at two degrees.

Log yield change for soybean production at two degrees warming is given in figure 4.3 for non irrigated and irrigated management regimes. The majority of non irrigated soybean cultivation occurs in the south eastern third of the country. There is a narrow band of impact stretching from Yunnan province to Tianjin. To the south east impacts are lower to mixed, with the least impact, and some positive effect, in Jiangsu province. There are two pockets of high impact to the north east in Heilongjiang province and Inner Mongolia, as well as some pockets of high impact in the center of the country. Irrigated soybean cultivation covers a much larger geographic extent, and shows minimal losses at two degrees warming. The eastern half of the country appears to show minimal gains to no changes. There are stronger positive impacts along the eastern border of Qinghai. There are pockets of log yield decrease along southern Tibet and along the Qinghai Sichuan border.

Log yield change for soybean production at three degrees warming is given in figure 4.4 for non irrigated and irrigated management regimes. Impacts for non irrigated soybean remain nearly unchanged for the south eastern portion of the country. Interestingly there are fewer pockets impacts through Sichuan, Qinghai, and Gansu at three degrees, and even signs of positive impacts through Qinghai. Overall the increase in warming from two degrees to three does not seem to generate a large change in crop impact.

Log yield change for rice production at two degrees warming is given in figure 4.5 for non irrigated and irrigated management regimes. For non irrigated rice cultivation is mainly found in the south eastern and north eastern regions of the country. Both of these regions show mixed results. In the northeast there are slight positive results along the eastern
portions of Heilongjiang, Jilin, and Liaoning provinces, with slight negative results to the east. To the south the positive results are mixed to the south east, with some negative results and some positive results in Sichuan province. For irrigated management the patterns look very similar in the areas where both regimes exist. There is a swath of negative impacts extending from Yunnan northeast to Inner Mongolia. There are negative impacts along the northern edge of Xinjiang province.

Log yield change for rice production at three degrees warming is given in figure 4.6 for non irrigated and irrigated management regimes. The patterns and intensity of impacts are nearly identical to those at two degrees warming.

Log yield change for sorghum production at two degrees warming is given in figure 4.7 for non irrigated and irrigated management regimes. Significant negative impacts are present over the majority of the cropped area, extending from the center of the country to the northeast. There are a few small areas of positive impact focused to the northeast in Heilongjiang and Inner Mongolia provinces, and towards the center of the country in the Gansu province. For irrigated sorghum the cropped extent extends across the majority of the eastern half of the country. Again we see yield reductions over the majority of the extent, though less pronounced than for non-irrigated yields. The highest impact occurs towards the southeast coastal provinces of Guangxi, Guangdong, and Fujian. There is a portion of cropped area in Xinjiang province that shows mild negative impact with a slight positive impact to the north and south of the province. A small band of positive impact is visible in the center of the country. Log yield change for sorghum production at three degrees warming is given in figure 4.8 for non irrigated and irrigated management regimes. The patterns of impact are geographically identical to those at 2 degrees with impacts presenting at a higher intensity for both positive and negative areas.

Log yield change for millet production at two degrees warming is given in figure 4.9 for non irrigated and irrigated management regimes. Non irrigated millet is mainly grown in the central and northeastern regions of the country. The entirety of the cropped extent
shows strong negative impacts, with the highest impacts occurring in the center of the country in Shaanxi province. The lowest impacts occur to the northeast in Heilongjiang province. Irrigated millet cultivation extends further south and sees a majority negative impact, though to a lesser extent than non irrigated. Regions of northern Heilongjiang and Gansu show a slight positive impact, as well as north Xinjiang province. Log yield change for millet production at three degrees warming is given in figure 4.10 for non irrigated and irrigated management regimes. Here we see a similar geographic pattern of warming for both irrigated and non irrigated, with a noticeably higher impact for non-irrigated management. Irrigated impacts remain nearly identical to those at two degrees warming.

Log yield change for potato production at two degrees warming is given in figure 4.11 for non irrigated and irrigated management regimes. For non irrigated potato cultivation there is a strong bifurcation in impacts, with the northwestern region of the cropped extent showing strong negative impacts and the southeastern areas showing very strong positive impacts. Interestingly this feature is reversed under irrigated management, with moderate negative impacts occurring to the southeast of the cultivated area, and neutral to positive impacts occurring along the northwest edge of the cultivated area. Log yield change for potato production at three degrees warming is given in figure 4.12 for non irrigated and irrigated management regimes, and remains nearly identical to those at two degrees warming.

4.3.2 Area Weighted Impacts

Area weighted impacts for corn at two degrees warming are given in figure 4.13. Overall there's a trend towards universally negative impacts in the southern cultivated regions, with mixed results to the north. The areas with the highest impact appear to be Yunnan, Sichuan, and Chongqing provinces in the south. There's a band of positive impacts along the southern border of Inner Mongolia. To the northwest the results are mixed, with some areas showing positive impacts, while others show negative impacts. Turning to 4.14 we
see the impacts at three degrees warming which show a similarly mixed result, however it appears that the intensities of both positive and negative impacts have increased.

Area weighted impacts for soy at two degrees warming are given in figure 4.15. The southeastern portion of the cultivated area appears to have neutral results, whereas the remainder of the cultivated area shows strongly negative impacts. To the northeast the results are particularly strongly negative along Inner Mongolia and Heilongjiang provinces. There are slightly positive results along the western portion of Xinjiang province to the north, and parts of Qinghai and Sichuan in the central portion of the country. The geographic pattern of impact at three degrees warming remains the same, as shown in figure 4.15, however there is an overall trend towards more negative, or in some cases less positive, impact.

Area weighted impacts for rice at two degrees warming are given in figure 4.17. The impact results are more minimal than other crops. There’s a tendency towards universally positive impacts in the south eastern portion of the country, with increasingly negative impacts as you move towards the north and northwest. The strongest negative impacts occur in Liaoning, Jilin, Heilongjiang, and Inner Mongolia provinces. There is also a noticeable patch of negative impacts to the north in Xinjiang province. The results at three degrees warming are given in figure 4.18 remain nearly identical.

Area weighted impacts for sorghum at two degrees warming are given in figure 4.19. Sorghum cultivation is mainly focused to the eastern portion of the country. Along the northern portion of the cultivated area the impacts are strongly negative. However, moving to the very far north of Heilongjiang province there is a strong band of positive impacts. To the south of the cultivated area the impacts are neutral to slightly negative, becoming increasingly negative as you move towards Guangxi and Guangdong provinces. There are portions of positive results in the center of the country in southern Gansu province, as well as a small pocket of positive results to the north of Xinjiang province. Figure 4.20 shows that the effects at three degrees warming are much more pronounced in both the negative
and positive areas.

Area weighted impacts for millet at two degrees warming are given in figure 4.21. These results resemble those of soybean, showing large portions of negative impacts in the north central portions of the country, with a pocket of positive impact to the north east and neutral to slightly negative impacts to the southeast. In figure 4.22 we see that the magnitude of the negative impacts increases across all cultivated areas compared to two degrees warming, and the positive impacts are reduced along northern Heilongjiang.

Area weighted impacts for potato at two degrees warming are given in figure 4.23. The impacts are strongly split between negative in the northwestern portion of the cultivated area and positive towards the southeastern portion. These results correlate strongly the topography of the country, with the negative results corresponding to the mid elevations and the positive results being seen at the lower elevations. In figure 4.24 we can see the same geographic pattern and nearly the same intensity of both positive and negative impacts.

4.3.3 Discussion

Overall these results show that nonirrigated crops are potentially more negatively impacted than irrigated crops. In most cases for both management techniques there are both positive and negative impacts. Many crops show strong patterns of impacts extending along a swath of land extending from Yunnan province to Beijing province. For soybeans, millet, and sorghum we see strong negative impacts along this path. However overall there is a tendency for higher impacts to the northwest of this swath and lower impacts to the southeast. This corresponds both to the elevation profile as well as the average temperature across the country, with higher elevations and cooler temperatures to the northwest and lower elevations and hotter temperatures to the southeast. These results suggest that impacts may actually be higher in areas that are generally cooler rather than in areas that are already warm.

When interpreting these results it is essential to note several assumptions and trace their
effect through the process. The first comes through the choice of methodology for generating growing degree days from monthly average temperatures generated from pattern scaling. The pattern scaled values used as inputs are generated from decadal monthly averages, averaged across the ensemble of models. Under this paradigm we are essentially looking at the average across multiple models, which will tend to smooth out very hot or very cold models. This is particularly prevalent for precipitation, where the models often diverge into very wet or very dry leaving an average change of around zero. Additionally, Thevenard (2011) showed that while it is possible to estimate standard deviations of daily temperature from the monthly deviations about the annual mean, it does increase the error in estimates of GDD.

By using the climate model ensemble 1980-2000 averages to represent the current temperature, and comparing them to the pattern scaling output at two and three degrees warming I have have attempted to minimize the bias introduced by the afore mentioned assumptions. However a key characteristic of the many of the response functions calculated in chapter 2 was nonlinearity in the response of log yield to both precipitation and temperature. If the pattern scaled synthetic growing degree days calculations for the current time period were significantly lower than the observed inputs used to simulate the crop-modeled data inputs used to estimate the yield response surfaces then I am potentially under estimating negative impacts in some areas, and over estimating positive impacts in other areas. Additionally, care should be taken to consider the uncertainty arising from forcing a non-linear additive statistical model with data that exceed the bounds of the sample on which it was fit.

Another key assumption has to do with the way in which the crop model handles irrigation. The model was run such that at every time step each crop received irrigated water equal to the water deficit. No consideration was given to whether that water would be available, or whether the irrigation infrastructure at a particular location would be capable of delivering that quantity of water. Essentially this amounts to having constant monitoring
of irrigated crops and titrating the perfect amount of water based on an instaneous need. Clearly this is not a realistic assumption, however it does provide for a very poignant insight. Despite having the ability to nearly perfectly adapt to changing conditions, there are still negative impacts across all six crop types in some regions. This point is crucial and cannot be understated. Under the scenarios tested here I find that while irrigated crops perform better than rainfed crops, irrigation cannot be relied on as the only method of adaptation against climate change.

4.4 Conclusions

In this chapter I have developed a methodology to combine climate model output generated through pattern scaling with a statistical representation of yield response to changes in climate for six staple crops in China. This chapter builds on the previous two chapters to provide a prototype path towards generating rapid risk based projections of impacts to regional crop yields from climate change. Growing season growing degree days were calculated using monthly temperature patterns following the simple pattern scaling approach outlined in chapter 1. Next I combined the growing degree day projections with cumulative precipitation patterns to simulate crop model fits estimated using the generalized additive model approach outlined in chapter 2. The resulting changes in yields were combined with a dataset of cropped acreage to determine areas at the highest risk of yield impacts from climate change.

Future work using this methodology will add the probabilistic component of the pattern scaling technique presented in chapter 1 to properly explore the uncertainty in the local climate response to a given amount of global mean temperature change. This will allow for a more robust characterization of the risk at each level of warming. Additional exploration of higher levels of global mean temperature change would be useful to highlight potential tipping points. A robust exploration of the uncertainty in the statistical yield response function is necessary as well.
Figure 4.1: Corn Yield Impact: Two Degrees Warming

Nonirrigated Corn Impact – Two Degrees Warming

Irrigated Corn Impact – Two Degrees Warming
Figure 4.2: Corn Yield Impact: Three Degrees Warming

Nonirrigated Corn Impact – Three Degrees Warming

Irrigated Corn Impact – Three Degrees Warming
Figure 4.3: Soybean Yield Impact: Two Degrees Warming
Figure 4.4: Soybean Yield Impact: Three Degrees Warming

Nonirrigated Soybean Impact – Three Degrees Warming

Irrigated Soybean Impact – Three Degrees Warming
Figure 4.5: Rice Yield Impact: Two Degrees Warming

Nonirrigated Rice Impact – Two Degrees Warming

Irrigated Rice Impact – Two Degrees Warming
Figure 4.6: Rice Yield Impact: Three Degrees Warming

Nonirrigated Rice Impact – Three Degrees Warming

Irrigated Rice Impact – Three Degrees Warming
Figure 4.7: Sorghum Yield Impact: Two Degrees Warming

Nonirrigated Sorghum Impact – Two Degrees Warming

Irrigated Sorghum Impact – Two Degrees Warming
Figure 4.8: Sorghum Yield Impact: Three Degrees Warming

Nonirrigated Sorghum Impact – Three Degrees Warming

Irrigated Sorghum Impact – Three Degrees Warming
Figure 4.9: Millet Yield Impact: Two Degrees Warming
Figure 4.10: Millet Yield Impact: Three Degrees Warming

Nonirrigated Millet Impact – Three Degrees Warming

Irrigated Millet Impact – Three Degrees Warming
Figure 4.11: Potato Yield Impact: Two Degrees Warming

Nonirrigated Potato Impact – Two Degrees Warming

Irrigated Potato Impact – Two Degrees Warming
Figure 4.12: Potato Yield Impact: Three Degrees Warming

Nonirrigated Potato Impact – Three Degrees Warming

Irrigated Potato Impact – Three Degrees Warming
Figure 4.13: Corn Yield Weighted Impact - Two Degrees Warming

Weighted Corn Impact – Two Degrees Warming

Log Yield Change

0.0
-0.1
-0.2
-0.3
-0.4
-0.5
Figure 4.14: Corn Yield Weighted Impact - Three Degrees Warming
Figure 4.15: Soybean Yield Weighted Impact - Two Degrees Warming
Figure 4.16: Soybean Yield Weighted Impact - Three Degrees Warming
Figure 4.17: Rice Yield Weighted Impact - Two Degrees Warming
Figure 4.18: Rice Yield Weighted Impact - Three Degrees Warming
Figure 4.19: Sorghum Yield Weighted Impact - Two Degrees Warming
Figure 4.20: Sorghum Yield Weighted Impact - Three Degrees Warming

Weighted Sorghum Impact – Three degrees warming

Log Yield Change

-0.5
-0.4
-0.3
-0.2
-0.1
0.0
Figure 4.21: Millet Yield Weighted Impact - Two Degrees Warming
Figure 4.22: Millet Yield Weighted Impact - Three Degrees Warming
Figure 4.23: Potato Yield Weighted Impact - Two Degrees Warming
Figure 4.24: Potato Yield Weighted Impact - Three Degrees Warming

Weighted Potato Impact – Three degrees warming

Log Yield Change

-1.0
-0.5
0.0
0.5

Longitude

Latitude
Chapter 5

Conclusions

Over the coming decades the society will be faced with the challenge of adapting agriculture to a warming world. Our existing agricultural system has developed over millennia of relatively stable climate. As population and global wealth increase, so will demand for food. The challenge of meeting this demand will require investment in innovative adaptation strategies. In order to maximize the return on adaptation spending it is crucial to understand where impacts are likely to be the greatest. Doing so requires a consistent modeling framework that addresses the spatial heterogeneity in changes in temperature and precipitation along with their associated uncertainty, and the nonlinear responses of crops to these changes. Furthermore this methodology must be appropriate across a wide variety of geographic settings, including those with limited data.

5.1 Research Summary

This dissertation develops a basic framework for moving towards a risk based approach to assessing the impact of climate change on crop yields. In the first chapter I develop a method for characterizing the uncertainty of an ensemble of climate models in their predictions of seasonal temperature and precipitation. To do this I combine a well known method for estimating the mean response of multiple climate models with a novel spatial statistic approach. Through this combination I am able to generate thousands of "synthetic" climate model fields, which retain the underlying spatial correlation structure found in the original ensemble. This results in a computationally efficient technique for quantifying the uncertainty of temperature and precipitation response to changes in global mean temperature. This approach assumes no dependency on a given emissions scenario, and therefore this approach could be easily integrated into an integrated assessment methodology.
In the second chapter I generate yield response surfaces for 16 irrigated and non irrigated crops in China. This is accomplished by applied a generalized additive model approach to the output of a process based climate model. These results highlight the nonlinear response to changes in growing degree days and cumulative across the beginning and end of the growing season, and provide a simple way to estimate the change in yield resulting from a change in temperature or precipitation. In the final chapter I combine results from the first and second chapter to assess the potential impact to yield of key crops in China.

In the final chapter I combine the statistical yield response surfaces with the pattern scaling approach outlined in the first two chapters to estimate the impacts of climate change over the cultivated areas of six staple crops in China. The results show that non irrigated crops are at the highest risk, however irrigated crops still see negative effects. This suggests that whir adaptation through enhanced irrigation could potentially provide some relief, it cannot be the only strategy in mitigating yield losses. The results vary in their geographic pattern depending on the crops, but generally show strong trends across a north south gradient, in particular for the central and eastern portions of the country. These results suggest that elevation and initial baseline climate have some affect on crop impacts.

5.2 Future Directions

It is my hope that this work will provide a proof-of-concept for new approaches to assessing the impact of climate change on agriculture. There are many logical next steps in support of this goal. The efforts to quickly analyze GCM output should be extended to include the most recent batch of models. However I would strongly urge any researcher pursuing this approach to consider the value of combining the output from multiple rounds of model intercomparison efforts. The contents of CMIP5 may not contain all the information in CMIP3. This warrants a rigorous investigation, and is likely beyond the scope of a single study.

A major concept that should be addressed is the need for joint distributions of tem-
perature and precipitation change. It is crucial when applying climate model output to agricultural impact studies that one considers the combined effect of changes in both variables and how they happen simultaneously. It should be readily apparent that the potential impact of hot and dry climates would be markedly different than those of hot and wet. The climate model emulator could be further developed through integrating with a simple climate model. This, along with the previously suggested points, would allow the most robust treatment of uncertainty in simulating the climate system, and would assure that any impact study was fully representative of all probable outcomes and risks.

The recent work done by the ISI-MIP provides a wealth of data to analyze. The generalized additive model approach I present would be perfectly well suited to analyze this data. A similar approach to the one taken in this work would allow one to estimate a similar response surface. The idea would be to include dummy variables in the estimation that included information on which crop model, climate model, and emissions pathway was being used. This would allow for estimates of global scale sensitivity to changes in climate variables as simulated against a wide variety of process models. Given the gridded nature of the dataset one would also be able to make use of robust standard error estimates to accommodate for spatial autocorrelation that would likely be present in the dataset.

Finally, in support of a true risk-based approach, these three chapters would be fully integrated such that the product of the last chapter was a spatially explicit map of the probability of changes in crop yield at a given level of warming. This would require simulating the GAM model as I have done here, however doing it for each of the 10,000 simulated runs, for each crop. By combining this with estimated derived from the ISI-MIP datasets one could rapidly assess the risk of loss in global agricultural production.
Appendix A

Spatial Model Results

A.1 Results

The patterns given in 2.1 and 2.2 represent the signal of climate change across models. This change also occurs in the context of the simulated natural variability in each model. Because this variability represents some amount of uncertainty in the projections, it is important to consider how it compares to the strength of the warming pattern. For temperature, the standard deviation of the inter-model average detrended decadal time series is depicted in figure A.5. These maps are shown for the study region of 60° N to 60° S. There is an increase in surface temperature variability over land surfaces compared to oceans, with the exception of a large zonal swath of variability over the equatorial pacific corresponding to El Niño / Southern Oscillation. The northern latitudes see a large amount of variability, in particular over Eurasia and northwestern Canada and Alaska. Seasonally the overall variability is the highest during the winter months, and the lowest during the summer months. Figure A.6 shows precipitation variability given in terms of percentages of the baseline 1980-2000 climatology. The pattern is mostly dominated by large degree of Saharan and sub-Saharan variability, which at times exceeds the base climatology values. This is indicative of both the high degree of natural variability over the region as well as model disagreement on precipitation dynamics over the region. There is also a higher degree of variability over the equatorial Pacific that mimics the temperature response.

A.1.1 Spatial Model Parameters

The behavior of the model is controlled by four parameters. The range of correlation is controlled by $\kappa_L^2$, which represents the autoregressive weight of the coefficients of the GMRF for level $L$. The relative weight of each level of the spatial model is controlled by $\alpha_L$. The
marginal variance of the entire process is given by $\rho$, and the noise, or measurement error, is given by $\sigma$. For each season I estimate a separate spatial process, thus allowing for structural differences between seasons. Temperature residuals were fit using a single level with 32 basis functions. Precipitation residuals were fit with two levels, with 32 and 64 basis functions, respectively. The parameters were fit using restricted maximum likelihood over a fixed search grid using the LatticeKrig package in R. There currently is no heuristic for choosing the number of levels or basis functions, and as such these choices were made based on trial and error. The parameter results for seasonal temperature precipitation residuals are given in tables A.1 and A.2. There is a moderate amount of variability in the parameters between seasons for both temperature and precipitation. A key observation is the behavior of the error and marginal variance with respect to the global mean temperature. For both temperature and precipitation, across all seasons, both of these variances increase with increasing global mean temperature. This reflects the heteroskedacity observed in the residuals. It also suggests that the variances could be parameterized in terms of the global mean temperature change rather than having a separate function for each level of global mean temperature change. This is beyond the scope of this dissertation, however it remains a priority for future work. The constant behavior of the $\alpha$ and $\kappa^2$ parameters is a function of the grid over which the restricted maximum likelihood was performed.

A.1.2 Global Risk Maps of Temperature Change

Using the 10,000 simulated GCM runs I calculated the probability of a grid cell experiencing more than a 2°, 3°, 4°, or 5° Celsius increase in local average temperature during each season for global temperature change of 2° and 3°. I use the terms high or low risk to describe areas of high or low probabilities, and the term "hot-spot" to denote an area of elevated risk compared to its surrounding areas. Across seasons and temperature thresholds there is a trend of increased risk over the continents and decreased risk over the oceans. Two notable exceptions are a large zonal swatch of elevated risk across the equatorial Pacific, which may
be owing to ENSO variability, and a large scale feature in the Northern Pacific to the south of the Aleutian chain. In general risk of warming increases in the northern latitudes. At 3° warming there is a notable risk increase at every threshold, in particular over land areas in the Southern Hemisphere. There is a marked increase in the total amount of land area at high risk of exceeding a 5° increase in local mean temperatures. During boreal winter the northern latitudes, in particular the Hudson Bay area, show very high risk of exceeding 5°. During the summer months this risk shifts towards the mid latitudes, with sections of the United States, Western and Southern Europe, and Central Asia all showing a high degree of risk of exceeding 5°. In the following section I outline the notable features for each season.

Winter

Figure 2.3 depicts exceedance probabilities for boreal winter at 2° global warming. Over North America the highest risk at each temperature threshold occurs over northeastern Canada and in particular over Hudson Bay, where the probability of exceeding 5° warming exceeds 80%. Lowest risk appears over the southeastern United States. A noticeable hot spot of risk is prevalent over the rocky mountain region of the western United States that persists in each panel. Over South America there is an area of increased risk over the northern region of the continent centered on Venezuela and Colombia. Elevated risk can also be seen along the length of the Andes at all but the highest temperature threshold. Over the African continent we see an area of elevated risk on the western third of the continent stretching from Algeria south to the Liberian coast. The middle of the continent sees a lower risk, with virtually no risk of exceeding 4° warming. Another area of concern is present across the eastern horn, centered on Kenya, and extending northeast into the Arabian Peninsula. At higher thresholds the risk dissipates over Eastern Africa but a strong signal remains over southern Saudi Arabia and Yemen. Western Europe has a relatively low level of risk, even at the lowest threshold, with risk increasing to the east. Most of Europe sees an extremely low level of risk of exceeding 4° warming.
occurs over Tibetan Plateau. This is the southernmost hotspot, with elevated risk even at the 5° threshold. Over Australia risk is concentrated towards the center of the continent and to the west.

Figure 2.7 depicts exceedance probabilities for 3° global warming. The most notable differences in risk between figures 2.3 and 2.7 occur in the 3° and 4° panels. At the 3° level there is a marked increase in risk over South America and Africa, with the largest changes occurring over Brazil and Central America, as well as over parts of southern India. Hot spots emerge at the 4° and 5° over the northern and southern edges of South America, as well as the western, eastern, and southern edges of Africa. A persistent hot spot is also present across the western edge of Australia. There is very high probability of exceeding 5° across the majority of Russia, as well as an isolated hot spot over the Tibetan plateau.

**Spring**

Figure 2.4 depicts exceedance probabilities for boreal spring for 2° global warming. Compared to winter season the areas of highest probability of exceeding 2° are shifted further south. Overall there is less land area at risk of exceeding 5° compared to the winter season. Over Hudson bay there is a lower risk across all seasons, with virtually no risk of exceeding 5° warming. The area of increased over the western United States appears larger, however the highest risk is shifted south into Mexico when compared to the winter season. Moving to South America the most notable feature is the large swatch of high probability of warming in western and southern Brazil in addition to the two hot spots from the winter season. Over Africa the three hotspots seen in the winter season still persist, however there is a slightly higher chance of warming to the interior of the continent. At higher temperatures the western and southern hot spots remain the most persistent features. Over Europe the spring patterns are similar to the winter patterns, however there is an elevated risk over parts of southern spain and portugal owing to the northern shift of the west African hotspot.

Figure 2.8 depicts exceedance probabilities for 3° Global Warming. The majority of
land surfaces show nearly a 100% chance of exceeding 2° local warming, and over an 80% chance of exceeding 3°. There are large increases in risk at the 3° threshold over portions of Central America, northern South America, Central Africa, the Mediterranean, and southern China. At the 4° the largest increases occur over western South America, and a contiguous swath stretching from the western coast of Africa to the northeast across central Asia and reaching to Mongolia. Both the western and Eastern coasts of the United States see large increases in risk. At the 5° threshold there is a large increase in risk over the mid-latitudes, most notably over southern Europe, Northern Africa and the Middle East, as well as areas over the Rocky Mountain and southeast regions of the United States.

**Summer**

Figure 2.5 depicts exceedance probabilities for boreal summer. The distinct signal over Northeastern Canada and Hudson bay is no longer present. Over North America the risk of exceeding each threshold is greater than in the spring for the majority of the continent, and greater than winter for the United States. However, northern areas of Canada show a lower risk of warming compared to winter. The hotspot over the western United States is larger than the winter season, and is shifted towards the Pacific Northwest. For South America the northern hotspot seen in figures 2.3 and 2.4 is less pronounced, and the strongest warming risk occurs over western Brazil. There is a notable increase in risk over Europe compared to other seasons, in particular over the western portion of the continent, persisting in the 4° panel and still noticeable in a grid cell over Spain at the 5° threshold. Over Africa there is a continued increase in risk over the central portions of the continent, which at the 2° threshold washes out the normal west, east, and south hotspots. The western and eastern hotspots appear as one larger area covering the majority of the northern parts of the continent, extending north into southern Europe. At higher thresholds this pattern splits with higher risk persisting over Algeria, as well as central Asia and the Arabian peninsula. There is a decrease in risk over the Tibetan plateau at higher thresholds compared to other
seasons. Australia has a notable transition to a northern band of high risk that persists fairly strongly up to 3°.

Figure 2.9 depicts exceedance probabilities for 3° global warming. The majority of land surfaces show nearly a 100% chance of exceeding 2° local warming, and over an 80% chance of exceeding 3°. At the 3° threshold there are large increases over the northern half of South America, central Africa extending to the Eastern Horn, southern India, as well as over the Korean Peninsula and Japan. At the 4° threshold there is a notable increase over Mexico stretching into the United States. Elevate Risk is uniformly present over most of Asia, with particularly high increases over southwestern China and India. Over Africa there are two areas of increased risk, one over the western portion, another over the southern portion. Risk increases at the 5° threshold retain the majority of the geographic patterns of the 4° threshold. Over Africa the hotspots are reduced in area to cover only the northwest and southern portions of the continent. Over Asia there is a very notable hotspot centered on the Tibetan plateau.

**Autumn**

Figure 2.5 shows probabilities for boreal summer. In general over north America the risk is more homogenous, especially across the United States. There is an area of slightly lower risk over the western coast of Canada. It is interesting to note that there is very little evidence of the winter hotspot over Hudson Bay. Though these results do not consider the correlation between seasons, this would suggest the possibility of an abruptly high amount of warming occurring during the seasonal transition from autumn to winter. At higher thresholds the low risk area extends further south into the western United States, and a small hotspot becomes notable in the central part of the country. Risk in South America extends over the majority of the continent, and shows the highest levels of risk in Brazil across all of the seasons. This is most notable in the 4° threshold panel. The elevated risk features that are shown in the summer panel over Western Europe persist in the Autumn
with slightly less strength, and a very low chance of exceeding the 4° threshold. Over Africa we see the decreased risk in the central part of the continent returning, and the general trend of higher risk in the North and South. As was noted for the summer maps, there is a large northern feature that splits to the west of Africa and to the east over the Arabian Peninsula at higher thresholds. The Tibetan hotspot is strong here, though slightly more localized than the winter season where it seems to reach its peak. Unlike the Hudson Bay hotspot, this feature is seen waxing and waning in size and strength across season, meaning it would be far less likely to see abrupt seasonal changes. The geographic extent of high risk over Australia is largest in autumn, covering the bulk of the continent.

Figure 2.10 depicts exceedance probabilities for 3° global warming. The majority of land surfaces show nearly a 100% chance of exceeding 2° local warming, and over an 80% chance of exceeding 3°. At the 3° threshold there is nearly homogeneous risk increase over all land surfaces. The largest exception occurs over Central Africa, with some elevated areas along the northern western and eastern coastline of South America, as well as Central America. At the 4° threshold the patterns of increase become a bit more heterogeneous. Elevated risk is apparent over parts of the southwestern United States and northern Mexico as well as the northern half of South America. Over Africa there are three hotspots over the western, northeastern, and southern parts of the continent. There is a large area of elevated risk extending from the Arabian peninsula to the northeast, through China and into southeastern Russia. Similar to previous seasons, at the 5° threshold the geographic patterns remain similar to the 4° threshold, with notable hotspots over the Tibetan Plateau and the Arabian Peninsula.

A.1.3 Global Risk Map of Precipitation Change

Risk maps for changes in precipitation at 2° and 3° warming are presented in Figures 2.11 through 2.18. These maps depict the probability of a grid cell experiencing a 10% or 25% reduction or increase in seasonally averaged precipitation. Unlike the temperature, precipi-
tation change over a given region may vary in both sign and intensity between models. The result in some regions are a nearly equal risk of increase and decrease in average precipitation. In general there is a tendency towards higher risk of drying across the subtropics into the lower edges of mid latitudes, and wetting over the tropics and high latitudes. Unlike local temperature, there is very little difference in risk between the 2° and 3° global warming scenarios. This is best visualized by comparing the shifts in regional densities of precipitation change between 2° and 3° warming shown in figuresA.15 through A.22 and discussed in section A.1.4. Here I discuss the features of these maps across seasons.

Winter

Figures 2.11 and 2.15 depict the probability of precipitation change for boreal winter. Unlike the temperature fields, the precipitation risk is much less dependent on ocean/land transitions, and more a function of latitude bands. This feature is most notable in the reduction threshold patterns, where we see elevated risk of decreased precipitation across the mid latitudes in both the southern and northern hemisphere. Over the northern half of North America there is a strong risk of increased precipitation, in particular over Hudson Bay, which sees over a 80% chance of a 25% increase in precipitation. Over the southern half of the continent there is a higher risk of reduced precipitation, with a hotspot prevalent over the pacific coast of Mexico. There is a pronounced area of risk of increased precipitation in the Equatorial Pacific to the west of South America which corresponds to the warming risk shown in figure 2.3. The majority of the signal over South America is weak, with a slight tendency towards more risk of increasing precipitation at the 10% threshold. Over Africa we see a large area of risk of increase over the Greater Horn region, which some areas showing high risk at the 25% level. There is a nearly equal probability across all thresholds over the Sahara, owing to the divergence of the GCM projections over this region. The risk becomes more defined at the 10% increase threshold to the northeast over the Mediterranean and western Turkey. There is a very strong signal of increased precipitation over the majority
of Russia and all but the southernmost region of China.

**Spring**

Figures 2.12 and 2.16 depict the probability of precipitation change for boreal spring. Overall the patterns of risk are geographically similar to the winter season, with some variation in the level of risk at each threshold. Over North America the risk of reduced precipitation is slightly stronger and more uniform than winter and shifted slightly to the north. The southwestern US sees a larger risk compared to the winter season, as the hotspot over Mexico shifts to the northwest. The risk in South America is nearly identical to winter, however the area over the Equatorial Pacific no longer extends over the western region of the continent. There is an increase in the risk of reduced precipitation over western and southern Europe compared to the winter. There is a lower risk of increased precipitation over the horn of Africa, while over the western coast there is a noticeable increase in the risk of decreased precipitation centered over Guinea, Sierra Leone, and Liberia. Over Russia there is a tendency towards higher risk of increased precipitation, however lower in intensity than winter.

**Summer**

Figures 2.13 and 2.17 depict the probability of precipitation change for boreal summer. In contrast to spring and winter there are much stronger signals of precipitation reduction over North America. The majority of the united states shows a tendency towards drying, and a high risk area is notable over southern Mexico into Central America and east across the Caribbean. This risk is strong at the 25% reduction threshold. To the west of South America, the equatorial hotspot is shifted slightly north when compared to the spring and winter seasons. Over Brazil the risk is more uniformly spread than previous seasons, and there is a slightly higher probability of reduced precipitation. Africa remains similar to previous seasons, with minimal signal towards the middle of the continent and a slight
tendency towards reduced precipitation to the north and south. Europe shows a strong risk of reduction across the entire continent. This remains strong at the 25% reduction level.

**Autumn**

Figures 2.14 and 2.18 depict the probability of precipitation change for boreal Autumn. Over North America there is a higher risk of increased precipitation than compared to summer over the majority of the continent, with a particularly high chance over northwestern Quebec. Over Mexico and Central America the risk of precipitation reduction is greatly reduced compared to summer. Over the North Pacific to the west of Mexico there is a large swath of elevated risk of increased precipitation extending north along the western coast of the US that remains strong at the 25% threshold. Over South America there is a slight tendency towards reduced precipitation over the majority of the continent. Offshore, the equatorial pacific band of increased precipitation remains present, with a band of reduced precipitation stretching northwest from the southern Chilean coast. A strong reduction signal remains present over Europe and Northern Africa, with particularly high risk over the strait of Gibraltar. For Central and Eastern Africa there is a strong chance of increased precipitation extending over the Arabian Peninsula and Arabian Sea. The majority of Eurasia sees a slight chance of increased precipitation, with higher risk over Eastern Russia.

**A.1.4 Regional Distribution Shifts**

For each season regional distributions of local temperature and precipitation change at 2° and 3° are calculated and compared in figures A.7 through A.22. For temperature the largest shifts in the median of the distributions occur in northern regions during boreal winter, with the Greenland and Northern Asian regions experience median shifts of over 2 degrees. Across all seasons the largest shifts occur in the northern hemisphere. Temperature variance also increases slightly across all seasons and all regions. For precipitation the distributions show a much smaller changes, with some regions showing increases and some
regions showing decreases. Precipitation variance increases in all regions across all seasons.

A.1.5 Model Fit

It is helpful to understand how the synthetic GCM distributions compare to the empirical distributions of the underlying model data. To address this I compare how much of the probability mass calculated by the synthetic distribution falls within or outside of the empirical distribution of the GCMs. To calculate this I look at the difference between the probability mass in each of the distributions in the middle 90%, and the upper and lower 5%.

Let $F_M$ and $F_S$ represent the cumulative distribution functions for the 29 modeled GCMs and the 10,000 synthetic GCMs, respectively, such that $F(x)$ represents the probability of obtaining a value less than or equal to $x$. Similarly, let $F_M^{-1}$ and $F_S^{-1}$ represent the inverse cumulative distribution functions for the model and synthetic distributions, respectively.

For each function, $F^{-1}(y)$ is a real number such that $F(x) = y$.

To compare the probability mass in the tails of the distribution I first compute the 5% and 95% quantiles of the model GCM distribution, $F_M^{-1}(0.05)$ and $F_M^{-1}(0.95)$. Next I compute the probability of obtaining a value less than or equal to these values in the synthetic distribution and subtract from that the GCM model quantile value:

$$
\delta F_{.05} = F_S \left( (F_M^{-1}(0.05)) - .05 \right) \quad (A.1)
$$

$$
\delta F_{.95} = F_S \left( (F_M^{-1}(0.95)) - .95 \right) \quad (A.2)
$$

To compare the middle 90% of the distributions I calculate the probability mass in the synthetic distributions corresponding to area between the 5% and 95% quantiles of the model distributions. I then subtract 0.90 from this value, such that:

$$
\delta F_{0.95-0.05} = F_S \left( (F_M^{-1}(0.95)) - F_S \left( (F_M^{-1}(0.05)) \right) - .90 \right) \quad (A.3)
$$
Tables A.3 to A.6 give the values for equations A.1 through A.3 for temperature, and tables A.7 to A.10 give the values for precipitation at 2° and 3° global mean temperature change, respectively. These values are given for land areas for each season over the 21 regions first given in Giorgi and Mearns (2002). The magnitude and sign of each value indicates the extent to which the synthetic GCM over or under predicts the corresponding region of the model GCM distribution. For the lower tail, $\delta F_{0.05}$, a positive value indicates there is more probability mass in the synthetic distribution tail and therefore the synthetic distribution has a wider lower tail, while a negative value indicates that the tail is narrower. The opposite is true for the upper tail, $\delta F_{0.95}$, where a negative value indicates there is more mass in the synthetic tail and therefore the distribution is wider at the upper tail. For the stable manifold, $\delta F_{0.95-0.05}$ represents the difference in probability mass of the central 90% of the distribution. A positive value indicates that the stable manifold of the synthetic distribution has less probability mass than the model distribution, and therefore covers a smaller range of likely values. A negative value indicates that the stable manifold of the synthetic distribution has more probability mass than the model distribution, and therefore implies a larger range of likely values. Plots of the synthetic GCM densities and model GCM densities for each individual region can be referenced in Figures A.24 through A.55.

**Temperature Distribution Comparisons**

For boreal winter at 2° the synthetic distribution has wider tails in all but the Amazon and Western Africa regions. The differences in the lower tail is most extreme over Central Asia, and the closest over Greenland. At the upper tails the synthetic distribution is wider in all but the Southeast Asia region, with the distributions differing the most over Central Asia and agreeing the most over Western Africa. The synthetic distribution predicts a wider stable manifold in every region but the Amazon and Western Africa. The distributions show the highest agreement over West Africa, Amazon, and Greenland, and least agreement over Central Asia, Sahara, and Central North America. At 3° the lower tails are wider over
Western and Eastern Africa, while the upper tails are wider over only Eastern Africa. The stable manifold is wider in every region with the exception of Western Africa. The highest overall agreement with the model distributions is found over Greenland, Western and Eastern Africa, and the lowest agreement is found over the Tibetan plateau and the Sahara.

For boreal spring at 2° the lower tails of the synthetic distributions are in general wider than the empirical, with exceptions over Western and Eastern Africa, Amazon, Greenland, and Southeast Asia. However the differences in lower tail probability mass between the distributions are overall lower than those in winter. In the upper tails the synthetic distributions are also wider in the majority of the regions. The synthetic distribution predicts a wider stable manifold in the majority of regions, with a narrower range in the Amazon, Western Africa, Eastern Africa, and Southeast Asia regions. The distributions have the highest agreement over East Africa and North Asia, and the least agreement over Southern South America. At 3° the lower tails are wider over Greenland, Western Africa, and Northern Asia. The upper tails are wider over Western Africa and Northern Asia. The stable manifold is wider over all regions with the exception of Western Africa and Northern Asia. The synthetic distribution has the highest overall agreement with the model distribution over Greenland and Northern Asia, with the least agreement over Central Asia and Northern Europe.

For boreal summer at 2° the synthetic distributions are in general wider than the empirical, with exceptions over Greenland, East and West Africa and Northern Asia. The upper tails are mixed, with about half of the regions wider and half of the regions narrower. Overall the predicted stable manifold is wider in the synthetic distributions with exceptions in the Amazon, Greenland, Northern Europe, Western Africa, and Eastern Africa regions. The highest overall agreement with the model distribution occurs over Eastern Africa and Northern Europe, and the least agreement over Southern South America and the whole of Australia. At 3° the lower tails are in general wider with exceptions over Greenland, Cen-
tral Asia, and Northern Asia. The upper tails show more variation with narrower tails over regions in the Western Hemisphere. Overall the stable manifold is wider, with exceptions over the Amazon, Greenland, and Western Africa regions. The synthetic distribution shows the highest agreement with the model distribution over Western and Eastern Africa, and the least agreement over Southern South America and Southern Australia.

For boreal autumn the synthetic distribution upper and lower tails are wider than the empirical across all regions. Overall the synthetic distribution predicts a wider stable manifold across all seasons, with the highest agreements over Amazon and Greenland, and lowest agreement over Southern Australia and Central Asia. At 3° the synthetic distribution upper and lower tails are wider than the empirical across all regions with the exception of Greenland. The stable manifold is also narrower across this region. The synthetic distribution shows the highest agreement with the model distribution over Greenland and Western Africa, and the least agreement over Central Asia and Southern Africa.

**Precipitation Distribution Comparisons**

For boreal summer at 2° the synthetic distribution lower tails are generally wider, with the exception of Greenland and Amazon. The upper tails are wider in all seasons, and overall the stable manifold of the distribution is wider across all regions. The highest agreement is seen over West Africa, Amazon and Greenland, while the least agreement is seen over Central Asia, Sahara, and Central North America. At 3° the synthetic distribution tails are wider in all regions with the exception of the Amazon. The upper tails are wider in all seasons, and overall the stable manifold is wider across all regions. The synthetic distribution shows the highest agreement with the model distribution over , and the least agreement over

For boreal spring at 2° the synthetic distribution lower tails are general wider, with the exception of the whole of Australia. The upper tails are wider in all regions, and overall the stable manifold of the distribution is wider across all regions. The highest agreement
is seen over Eastern Africa, Northern Asia, and the Amazon, while the least agreement is seen over Southern South America, the Tibetan Plateau, and Central North America. At 3° the synthetic distribution lower tails are wider in all regions but Northern Asia, while the upper tails and stable manifold are wider in all regions. The synthetic distribution shows the highest agreement with the model distribution over Greenland and Northern Asia, and the least agreement over Northern Europe and Central Asia.

For boreal summer at 2° the synthetic distribution upper tails, lower tails, and stable manifold are all wider than the model GCMs. The highest agreement is seen over Eastern Africa, Northern Europe and the Mediterranean. The least agreement is seen over Southern South America, and the whole of Australia. At 3° the lower tails of the distribution are wider over all regions but Northern Europe. The upper tails and stable manifold are wider over all regions. The synthetic distribution shows the highest agreement with the model distribution over Western Africa and Eastern Africa, and the least agreement over Southern Australia and Southern South America.

For boreal autumn at 2° the synthetic distribution lower and upper tails are wider in all regions but the Amazon. The same holds for the stable manifold. The highest agreement occurs over the Amazon, Greenland, and Western Africa. The lowest agreement occurs over Southern Australia, Central Asia, and Southern South America. At 3° the lower tails are wider in all regions with the exception of the Amazon, while the upper tails are wider in all regions but the Amazon and Eastern Africa. The stable manifold is wider in all regions but the Amazon. The synthetic distribution shows the highest agreement with the model distribution over Greenland and Western Africa, and the least agreement over Southern Africa and Central America.
Figure A.1: Regional Temperature Residuals from Pattern Scaling compared to Global Mean Temperature Change

AMZ

CNA

EAS

TIB
Table A.1: Spatial Model Parameters for Temperature

$$\Delta T^G = \begin{array}{c|c|c|c|c|c|c}
\text{DJF} & \text{MAM} & \text{JJA} & \text{SON} \\
\hline
\sigma & 0.971 & 1.182 & 0.843 & 1.039 & 1.049 & 1.332 \\
\rho & 3.197 & 3.761 & 2.648 & 3.07 & 3.075 & 3.678 \\
\end{array}$$

Table A.2: Spatial Model Parameters for Precipitation

$$\Delta T^G = \begin{array}{c|c|c|c|c|c|c}
\text{DJF} & \text{MAM} & \text{JJA} & \text{SON} \\
\hline
\alpha_1 & 0.67 & 0.67 & 0.67 & 0.67 & 0.67 & 0.67 \\
\alpha_2 & 0.33 & 0.33 & 0.33 & 0.33 & 0.33 & 0.33 \\
\sigma & 0.869 & 1.035 & 0.841 & 0.966 & 0.925 & 1.137 \\
\rho & 3.45 & 3.998 & 3.106 & 3.512 & 3.5 & 4.203 \\
\end{array}$$
Figure A.2: Regional Precipitation Residuals from Pattern Scaling compared to Global Mean Temperature Change
Figure A.3: Grid Cell Temperature Residuals from Pattern Scaling compared to Global Mean Temperature Change
Figure A.4: Regional Precipitation Residuals from Pattern Scaling compared to Global Mean Temperature Change
Table A.3: Comparison of synthetic and empirical distribution functions for seasonal average temperature at two degrees global warming, DJF / MAM

<table>
<thead>
<tr>
<th>Region</th>
<th>DJF</th>
<th>MAM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\delta F_{0.05}$</td>
<td>$\delta F_{0.95}$</td>
</tr>
<tr>
<td>NAU</td>
<td>0.094</td>
<td>-0.12</td>
</tr>
<tr>
<td>SAU</td>
<td>0.19</td>
<td>-0.099</td>
</tr>
<tr>
<td>AMZ</td>
<td>-0.026</td>
<td>0.014</td>
</tr>
<tr>
<td>SSA</td>
<td>0.17</td>
<td>-0.12</td>
</tr>
<tr>
<td>CAM</td>
<td>0.068</td>
<td>-0.1</td>
</tr>
<tr>
<td>WNA</td>
<td>0.05</td>
<td>-0.14</td>
</tr>
<tr>
<td>CNA</td>
<td>0.2</td>
<td>-0.18</td>
</tr>
<tr>
<td>ENA</td>
<td>0.17</td>
<td>-0.16</td>
</tr>
<tr>
<td>GRL</td>
<td>0.0033</td>
<td>-0.041</td>
</tr>
<tr>
<td>MED</td>
<td>0.16</td>
<td>-0.059</td>
</tr>
<tr>
<td>NEU</td>
<td>0.14</td>
<td>-0.054</td>
</tr>
<tr>
<td></td>
<td>0.0022</td>
<td>0.014</td>
</tr>
<tr>
<td>WAF</td>
<td>-0.046</td>
<td>-0.009</td>
</tr>
<tr>
<td>EAF</td>
<td>0.07</td>
<td>-0.015</td>
</tr>
<tr>
<td>SAF</td>
<td>0.027</td>
<td>-0.17</td>
</tr>
<tr>
<td>SAH</td>
<td>0.26</td>
<td>-0.18</td>
</tr>
<tr>
<td>SEA</td>
<td>0.059</td>
<td>0.017</td>
</tr>
<tr>
<td>EAS</td>
<td>0.17</td>
<td>-0.16</td>
</tr>
<tr>
<td>SAS</td>
<td>0.16</td>
<td>-0.008</td>
</tr>
<tr>
<td>CAS</td>
<td>0.25</td>
<td>-0.19</td>
</tr>
<tr>
<td>TIB</td>
<td>0.19</td>
<td>-0.14</td>
</tr>
<tr>
<td>NAS</td>
<td>0.061</td>
<td>-0.011</td>
</tr>
</tbody>
</table>
Table A.4: Comparison of synthetic and empirical distribution functions for seasonal average temperature at two degrees global warming, JJA / SON

<table>
<thead>
<tr>
<th>Region</th>
<th>JJA $\delta F_{.05}$</th>
<th>$\delta F_{.95}$</th>
<th>$\delta F_{.95-.05}$</th>
<th>SON $\delta F_{.05}$</th>
<th>$\delta F_{.95}$</th>
<th>$\delta F_{.95-.05}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAU</td>
<td>0.095</td>
<td>-0.18</td>
<td>-0.28</td>
<td>0.13</td>
<td>-0.25</td>
<td>-0.39</td>
</tr>
<tr>
<td>SAU</td>
<td>0.11</td>
<td>-0.078</td>
<td>-0.19</td>
<td>0.22</td>
<td>-0.25</td>
<td>-0.47</td>
</tr>
<tr>
<td>AMZ</td>
<td>-0.0068</td>
<td>0.044</td>
<td>0.051</td>
<td>0.045</td>
<td>-7e-04</td>
<td>-0.045</td>
</tr>
<tr>
<td>SSA</td>
<td>0.2</td>
<td>-0.17</td>
<td>-0.36</td>
<td>0.25</td>
<td>-0.15</td>
<td>-0.4</td>
</tr>
<tr>
<td>CAM</td>
<td>0.044</td>
<td>-0.011</td>
<td>-0.055</td>
<td>0.16</td>
<td>-0.12</td>
<td>-0.28</td>
</tr>
<tr>
<td>WNA</td>
<td>0.057</td>
<td>0.0056</td>
<td>-0.051</td>
<td>0.14</td>
<td>-0.21</td>
<td>-0.35</td>
</tr>
<tr>
<td>CNA</td>
<td>0.086</td>
<td>0.03</td>
<td>-0.056</td>
<td>0.19</td>
<td>-0.18</td>
<td>-0.37</td>
</tr>
<tr>
<td>ENA</td>
<td>0.052</td>
<td>-0.02</td>
<td>-0.072</td>
<td>0.21</td>
<td>-0.13</td>
<td>-0.34</td>
</tr>
<tr>
<td>GRL</td>
<td>-0.032</td>
<td>0.048</td>
<td>0.081</td>
<td>0.059</td>
<td>-0.049</td>
<td>-0.11</td>
</tr>
<tr>
<td>MED</td>
<td>0.025</td>
<td>0.0043</td>
<td>-0.021</td>
<td>0.16</td>
<td>-0.092</td>
<td>-0.26</td>
</tr>
<tr>
<td>NEU</td>
<td>0.0022</td>
<td>0.014</td>
<td>0.012</td>
<td>0.23</td>
<td>-0.036</td>
<td>-0.26</td>
</tr>
<tr>
<td>WAF</td>
<td>-2e-04</td>
<td>0.048</td>
<td>0.048</td>
<td>0.095</td>
<td>-0.049</td>
<td>-0.14</td>
</tr>
<tr>
<td>EAF</td>
<td>-0.019</td>
<td>-6e-04</td>
<td>0.018</td>
<td>0.096</td>
<td>-0.12</td>
<td>-0.21</td>
</tr>
<tr>
<td>SAF</td>
<td>0.095</td>
<td>-0.1</td>
<td>-0.2</td>
<td>0.21</td>
<td>-0.18</td>
<td>-0.39</td>
</tr>
<tr>
<td>SAH</td>
<td>0.027</td>
<td>-0.014</td>
<td>-0.041</td>
<td>0.19</td>
<td>-0.1</td>
<td>-0.29</td>
</tr>
<tr>
<td>SEA</td>
<td>0.05</td>
<td>-0.014</td>
<td>-0.064</td>
<td>0.22</td>
<td>-0.15</td>
<td>-0.37</td>
</tr>
<tr>
<td>EAS</td>
<td>0.029</td>
<td>0.0012</td>
<td>-0.028</td>
<td>0.071</td>
<td>-0.14</td>
<td>-0.21</td>
</tr>
<tr>
<td>SAS</td>
<td>0.059</td>
<td>-0.029</td>
<td>-0.089</td>
<td>0.2</td>
<td>-0.12</td>
<td>-0.32</td>
</tr>
<tr>
<td>CAS</td>
<td>0.031</td>
<td>-0.055</td>
<td>-0.086</td>
<td>0.21</td>
<td>-0.28</td>
<td>-0.49</td>
</tr>
<tr>
<td>TIB</td>
<td>0.06</td>
<td>0.009</td>
<td>-0.051</td>
<td>0.16</td>
<td>-0.24</td>
<td>-0.4</td>
</tr>
<tr>
<td>NAS</td>
<td>-0.034</td>
<td>0.048</td>
<td>0.082</td>
<td>0.11</td>
<td>-0.092</td>
<td>-0.2</td>
</tr>
</tbody>
</table>
Table A.5: Comparison of synthetic and empirical distribution functions for seasonal average temperature at three degrees warming, DJF / MAM

<table>
<thead>
<tr>
<th>Region</th>
<th>DJF $\delta F_{.05}$</th>
<th>$\delta F_{.95}$</th>
<th>$\delta F_{.95-.05}$</th>
<th>MAM $\delta F_{.05}$</th>
<th>$\delta F_{.95}$</th>
<th>$\delta F_{.95-.05}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAU</td>
<td>0.14</td>
<td>-0.16</td>
<td>-0.31</td>
<td>0.033</td>
<td>-0.18</td>
<td>-0.22</td>
</tr>
<tr>
<td>SAU</td>
<td>0.16</td>
<td>-0.13</td>
<td>-0.29</td>
<td>0.068</td>
<td>-0.13</td>
<td>-0.2</td>
</tr>
<tr>
<td>AMZ</td>
<td>0.11</td>
<td>-0.0029</td>
<td>-0.11</td>
<td>0.066</td>
<td>0.017</td>
<td>-0.049</td>
</tr>
<tr>
<td>SSA</td>
<td>0.26</td>
<td>-0.011</td>
<td>-0.27</td>
<td>0.15</td>
<td>0.028</td>
<td>-0.12</td>
</tr>
<tr>
<td>CAM</td>
<td>0.09</td>
<td>-0.12</td>
<td>-0.21</td>
<td>0.12</td>
<td>-0.058</td>
<td>-0.18</td>
</tr>
<tr>
<td>WNA</td>
<td>0.13</td>
<td>-0.1</td>
<td>-0.23</td>
<td>0.092</td>
<td>-0.0024</td>
<td>-0.094</td>
</tr>
<tr>
<td>CNA</td>
<td>0.17</td>
<td>-0.11</td>
<td>-0.27</td>
<td>0.081</td>
<td>-0.089</td>
<td>-0.17</td>
</tr>
<tr>
<td>ENA</td>
<td>0.13</td>
<td>-0.16</td>
<td>-0.29</td>
<td>0.095</td>
<td>-0.09</td>
<td>-0.18</td>
</tr>
<tr>
<td>GRL</td>
<td>0.03</td>
<td>-0.012</td>
<td>-0.042</td>
<td>-0.0052</td>
<td>-0.012</td>
<td>-0.0071</td>
</tr>
<tr>
<td>MED</td>
<td>0.15</td>
<td>-0.17</td>
<td>-0.32</td>
<td>0.046</td>
<td>-0.044</td>
<td>-0.09</td>
</tr>
<tr>
<td>NEU</td>
<td>0.11</td>
<td>-0.35</td>
<td>-0.46</td>
<td>0.07</td>
<td>-0.26</td>
<td>-0.33</td>
</tr>
<tr>
<td>WAF</td>
<td>-0.05</td>
<td>0.022</td>
<td>0.072</td>
<td>-0.037</td>
<td>0.0099</td>
<td>0.047</td>
</tr>
<tr>
<td>EAF</td>
<td>-0.021</td>
<td>-0.084</td>
<td>-0.064</td>
<td>0.078</td>
<td>-0.0058</td>
<td>-0.084</td>
</tr>
<tr>
<td>SAF</td>
<td>0.15</td>
<td>-0.041</td>
<td>-0.19</td>
<td>0.14</td>
<td>-0.068</td>
<td>-0.21</td>
</tr>
<tr>
<td>SAH</td>
<td>0.13</td>
<td>-0.26</td>
<td>-0.39</td>
<td>0.074</td>
<td>-0.18</td>
<td>-0.26</td>
</tr>
<tr>
<td>SEA</td>
<td>0.063</td>
<td>-0.12</td>
<td>-0.18</td>
<td>0.051</td>
<td>0.0056</td>
<td>-0.045</td>
</tr>
<tr>
<td>EAS</td>
<td>0.087</td>
<td>-0.17</td>
<td>-0.26</td>
<td>0.042</td>
<td>-0.066</td>
<td>-0.11</td>
</tr>
<tr>
<td>SAS</td>
<td>0.12</td>
<td>-0.18</td>
<td>-0.29</td>
<td>0.27</td>
<td>-0.085</td>
<td>-0.36</td>
</tr>
<tr>
<td>CAS</td>
<td>0.27</td>
<td>-0.2</td>
<td>-0.47</td>
<td>0.14</td>
<td>-0.12</td>
<td>-0.26</td>
</tr>
<tr>
<td>TIB</td>
<td>0.16</td>
<td>-0.26</td>
<td>-0.42</td>
<td>0.16</td>
<td>-0.082</td>
<td>-0.24</td>
</tr>
<tr>
<td>NAS</td>
<td>0.13</td>
<td>-0.027</td>
<td>-0.16</td>
<td>-0.0015</td>
<td>0.027</td>
<td>0.028</td>
</tr>
</tbody>
</table>
Table A.6: Comparison of synthetic and empirical distribution functions for seasonal average temperature at three degrees warming, JJA / SON

<table>
<thead>
<tr>
<th>Region</th>
<th>DJF</th>
<th>MAM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\Delta F_{0.05}$</td>
<td>$\Delta F_{0.95}$</td>
</tr>
<tr>
<td>NAU 0.19</td>
<td>-0.14</td>
<td>-0.33</td>
</tr>
<tr>
<td>SAU</td>
<td>0.1</td>
<td>-0.3</td>
</tr>
<tr>
<td>AMZ</td>
<td>0.027</td>
<td>0.043</td>
</tr>
<tr>
<td>SSA</td>
<td>0.19</td>
<td>-0.1</td>
</tr>
<tr>
<td>CAM</td>
<td>0.16</td>
<td>-0.088</td>
</tr>
<tr>
<td>WNA</td>
<td>0.025</td>
<td>0.021</td>
</tr>
<tr>
<td>CNA</td>
<td>0.092</td>
<td>0.041</td>
</tr>
<tr>
<td>ENA</td>
<td>0.1</td>
<td>0.0012</td>
</tr>
<tr>
<td>GRL</td>
<td>-0.025</td>
<td>0.049</td>
</tr>
<tr>
<td>MED 0.065</td>
<td>-0.017</td>
<td>-0.081</td>
</tr>
<tr>
<td>NEU</td>
<td>0.075</td>
<td>-0.037</td>
</tr>
<tr>
<td>WAF</td>
<td>0.0027</td>
<td>0.0087</td>
</tr>
<tr>
<td>EAF</td>
<td>0.0044</td>
<td>-0.016</td>
</tr>
<tr>
<td>SAF</td>
<td>0.12</td>
<td>-0.13</td>
</tr>
<tr>
<td>SAH</td>
<td>0.066</td>
<td>-0.094</td>
</tr>
<tr>
<td>SEA</td>
<td>0.11</td>
<td>-0.011</td>
</tr>
<tr>
<td>EAS</td>
<td>0.05</td>
<td>-0.024</td>
</tr>
<tr>
<td>SAS</td>
<td>0.13</td>
<td>-0.055</td>
</tr>
<tr>
<td>CAS</td>
<td>-0.0099</td>
<td>-0.13</td>
</tr>
<tr>
<td>TIB</td>
<td>0.048</td>
<td>-0.038</td>
</tr>
<tr>
<td>NAS</td>
<td>-0.039</td>
<td>0.044</td>
</tr>
</tbody>
</table>
Table A.7: Comparison of synthetic and empirical distribution functions for seasonal average precipitation at two degrees warming, JJA / SON

<table>
<thead>
<tr>
<th>Region</th>
<th>( \delta F_{0.05} )</th>
<th>( \delta F_{0.95} )</th>
<th>( \delta F_{0.95} - \delta F_{0.05} )</th>
<th>( \delta F_{0.05} )</th>
<th>( \delta F_{0.95} )</th>
<th>( \delta F_{0.95} - \delta F_{0.05} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAU</td>
<td>0.2</td>
<td>-0.19</td>
<td>-0.38</td>
<td>0.084</td>
<td>-0.12</td>
<td>-0.2</td>
</tr>
<tr>
<td>SAU</td>
<td>0.21</td>
<td>-0.21</td>
<td>-0.42</td>
<td>-0.003</td>
<td>-0.12</td>
<td>-0.12</td>
</tr>
<tr>
<td>AMZ</td>
<td>-0.021</td>
<td>-0.047</td>
<td>-0.027</td>
<td>0.086</td>
<td>-0.15</td>
<td>-0.24</td>
</tr>
<tr>
<td>SSA</td>
<td>0.13</td>
<td>-0.29</td>
<td>-0.42</td>
<td>0.11</td>
<td>-0.23</td>
<td>-0.35</td>
</tr>
<tr>
<td>CAM</td>
<td>0.097</td>
<td>-0.18</td>
<td>-0.27</td>
<td>0.054</td>
<td>-0.22</td>
<td>-0.28</td>
</tr>
<tr>
<td>WNA</td>
<td>0.14</td>
<td>-0.12</td>
<td>-0.25</td>
<td>0.079</td>
<td>-0.19</td>
<td>-0.27</td>
</tr>
<tr>
<td>CNA</td>
<td>0.19</td>
<td>-0.18</td>
<td>-0.38</td>
<td>0.026</td>
<td>-0.071</td>
<td>-0.097</td>
</tr>
<tr>
<td>ENA</td>
<td>0.14</td>
<td>-0.1</td>
<td>-0.24</td>
<td>0.072</td>
<td>-0.072</td>
<td>-0.14</td>
</tr>
<tr>
<td>GRL</td>
<td>-0.01</td>
<td>-0.018</td>
<td>-0.0075</td>
<td>0.13</td>
<td>-0.053</td>
<td>-0.18</td>
</tr>
<tr>
<td>MED</td>
<td>0.16</td>
<td>-0.2</td>
<td>-0.36</td>
<td>0.11</td>
<td>-0.17</td>
<td>-0.28</td>
</tr>
<tr>
<td>NEU</td>
<td>0.25</td>
<td>-0.18</td>
<td>-0.44</td>
<td>0.067</td>
<td>-0.11</td>
<td>-0.18</td>
</tr>
<tr>
<td>WAF</td>
<td>0.16</td>
<td>-0.17</td>
<td>-0.33</td>
<td>0.16</td>
<td>-0.17</td>
<td>-0.33</td>
</tr>
<tr>
<td>EAF</td>
<td>0.11</td>
<td>-0.24</td>
<td>-0.35</td>
<td>0.12</td>
<td>-0.19</td>
<td>-0.31</td>
</tr>
<tr>
<td>SAF</td>
<td>0.24</td>
<td>-0.16</td>
<td>-0.4</td>
<td>0.19</td>
<td>-0.2</td>
<td>-0.4</td>
</tr>
<tr>
<td>SAH</td>
<td>0.065</td>
<td>-0.038</td>
<td>-0.1</td>
<td>0.066</td>
<td>-0.27</td>
<td>-0.34</td>
</tr>
<tr>
<td>SEA</td>
<td>0.28</td>
<td>-0.083</td>
<td>-0.36</td>
<td>0.18</td>
<td>-0.18</td>
<td>-0.37</td>
</tr>
<tr>
<td>EAS</td>
<td>0.057</td>
<td>-0.042</td>
<td>-0.1</td>
<td>0.13</td>
<td>-0.22</td>
<td>-0.35</td>
</tr>
<tr>
<td>SAS</td>
<td>0.17</td>
<td>-0.29</td>
<td>-0.46</td>
<td>0.12</td>
<td>-0.076</td>
<td>-0.2</td>
</tr>
<tr>
<td>CAS</td>
<td>0.067</td>
<td>-0.13</td>
<td>-0.19</td>
<td>0.026</td>
<td>-0.16</td>
<td>-0.18</td>
</tr>
<tr>
<td>TIB</td>
<td>0.16</td>
<td>-0.046</td>
<td>-0.2</td>
<td>0.19</td>
<td>-0.24</td>
<td>-0.43</td>
</tr>
<tr>
<td>NAS</td>
<td>0.027</td>
<td>-0.055</td>
<td>-0.083</td>
<td>-0.013</td>
<td>-0.082</td>
<td>-0.069</td>
</tr>
</tbody>
</table>
Table A.8: Comparison of synthetic and empirical distribution functions for seasonal average precipitation at two degrees warming, JJA / SON

<table>
<thead>
<tr>
<th>Region</th>
<th>$\delta F_{0.05}$</th>
<th>$\delta F_{0.95}$</th>
<th>$\delta F_{0.95-0.05}$</th>
<th>$\delta F_{0.05}$</th>
<th>$\delta F_{0.95}$</th>
<th>$\delta F_{0.95-0.05}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAU</td>
<td>0.15</td>
<td>-0.23</td>
<td>-0.38</td>
<td>0.22</td>
<td>-0.19</td>
<td>-0.41</td>
</tr>
<tr>
<td>SAU</td>
<td>0.12</td>
<td>-0.094</td>
<td>-0.22</td>
<td>0.24</td>
<td>-0.17</td>
<td>-0.41</td>
</tr>
<tr>
<td>AMZ</td>
<td>0.082</td>
<td>-0.049</td>
<td>-0.13</td>
<td>-0.029</td>
<td>0.05</td>
<td>0.079</td>
</tr>
<tr>
<td>SSA</td>
<td>0.088</td>
<td>-0.056</td>
<td>-0.14</td>
<td>0.16</td>
<td>-0.18</td>
<td>-0.34</td>
</tr>
<tr>
<td>CAM</td>
<td>0.081</td>
<td>-0.24</td>
<td>-0.33</td>
<td>0.0071</td>
<td>-0.092</td>
<td>-0.099</td>
</tr>
<tr>
<td>WNA</td>
<td>0.14</td>
<td>-0.34</td>
<td>-0.49</td>
<td>0.22</td>
<td>-0.27</td>
<td>-0.49</td>
</tr>
<tr>
<td>CNA</td>
<td>0.087</td>
<td>-0.16</td>
<td>-0.25</td>
<td>0.21</td>
<td>-0.16</td>
<td>-0.37</td>
</tr>
<tr>
<td>ENA</td>
<td>0.08</td>
<td>-0.22</td>
<td>-0.3</td>
<td>0.21</td>
<td>-0.15</td>
<td>-0.36</td>
</tr>
<tr>
<td>GRL</td>
<td>0.038</td>
<td>-0.19</td>
<td>-0.23</td>
<td>0.041</td>
<td>-0.17</td>
<td>-0.21</td>
</tr>
<tr>
<td>MED</td>
<td>0.23</td>
<td>-0.22</td>
<td>-0.45</td>
<td>0.17</td>
<td>-0.24</td>
<td>-0.4</td>
</tr>
<tr>
<td>NEU</td>
<td>0.071</td>
<td>-0.1</td>
<td>-0.17</td>
<td>0.079</td>
<td>-0.17</td>
<td>-0.25</td>
</tr>
<tr>
<td>WAF</td>
<td>0.091</td>
<td>-0.13</td>
<td>-0.22</td>
<td>0.13</td>
<td>-0.013</td>
<td>-0.14</td>
</tr>
<tr>
<td>EAF</td>
<td>0.22</td>
<td>-0.26</td>
<td>-0.48</td>
<td>0.069</td>
<td>-0.01</td>
<td>-0.079</td>
</tr>
<tr>
<td>SAF</td>
<td>0.2</td>
<td>-0.24</td>
<td>-0.43</td>
<td>0.08</td>
<td>-0.23</td>
<td>-0.31</td>
</tr>
<tr>
<td>SAH</td>
<td>0.13</td>
<td>-0.2</td>
<td>-0.34</td>
<td>0.056</td>
<td>-0.17</td>
<td>-0.23</td>
</tr>
<tr>
<td>SEA</td>
<td>0.099</td>
<td>-0.16</td>
<td>-0.26</td>
<td>0.15</td>
<td>-0.042</td>
<td>-0.2</td>
</tr>
<tr>
<td>EAS</td>
<td>0.25</td>
<td>-0.2</td>
<td>-0.45</td>
<td>0.12</td>
<td>-0.073</td>
<td>-0.2</td>
</tr>
<tr>
<td>SAS</td>
<td>0.13</td>
<td>-0.03</td>
<td>-0.16</td>
<td>0.1</td>
<td>0.0082</td>
<td>-0.092</td>
</tr>
<tr>
<td>CAS</td>
<td>0.12</td>
<td>-0.2</td>
<td>-0.32</td>
<td>0.079</td>
<td>-0.077</td>
<td>-0.16</td>
</tr>
<tr>
<td>TIB</td>
<td>0.057</td>
<td>-0.17</td>
<td>-0.23</td>
<td>0.19</td>
<td>-0.17</td>
<td>-0.36</td>
</tr>
<tr>
<td>NAS</td>
<td>0.21</td>
<td>-0.16</td>
<td>-0.38</td>
<td>0.08</td>
<td>-0.12</td>
<td>-0.2</td>
</tr>
</tbody>
</table>
Figure A.5: Average Patterns of Seasonal Temperature Natural Variability
Figure A.6: Average Patterns of Seasonal Precipitation Natural Variability
Table A.9: Comparison of synthetic and empirical distribution functions for seasonal average precipitation at three degrees warming, DJF / MAM

<table>
<thead>
<tr>
<th>Region</th>
<th>DJF</th>
<th>MAM</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\delta F_{0.05}$</td>
<td>$\delta F_{0.95}$</td>
<td>$\delta F_{0.95-0.05}$</td>
<td>$\delta F_{0.05}$</td>
<td>$\delta F_{0.95}$</td>
<td>$\delta F_{0.95-0.05}$</td>
</tr>
<tr>
<td>NAU</td>
<td>0.23</td>
<td>-0.13</td>
<td>-0.36</td>
<td>0.23</td>
<td>-0.077</td>
<td>-0.3</td>
</tr>
<tr>
<td>SAU</td>
<td>0.11</td>
<td>-0.24</td>
<td>-0.36</td>
<td>0.091</td>
<td>-0.22</td>
<td>-0.31</td>
</tr>
<tr>
<td>AMZ</td>
<td>-0.026</td>
<td>-0.11</td>
<td>-0.087</td>
<td>0.095</td>
<td>-0.18</td>
<td>-0.28</td>
</tr>
<tr>
<td>SSA</td>
<td>0.15</td>
<td>-0.24</td>
<td>-0.4</td>
<td>0.15</td>
<td>-0.27</td>
<td>-0.43</td>
</tr>
<tr>
<td>CAM</td>
<td>0.069</td>
<td>-0.2</td>
<td>-0.27</td>
<td>0.14</td>
<td>-0.26</td>
<td>-0.4</td>
</tr>
<tr>
<td>WNA</td>
<td>0.32</td>
<td>-0.079</td>
<td>-0.4</td>
<td>0.17</td>
<td>-0.18</td>
<td>-0.35</td>
</tr>
<tr>
<td>CNA</td>
<td>0.13</td>
<td>-0.12</td>
<td>-0.25</td>
<td>0.0076</td>
<td>-0.2</td>
<td>-0.21</td>
</tr>
<tr>
<td>ENA</td>
<td>0.15</td>
<td>-0.21</td>
<td>-0.36</td>
<td>0.082</td>
<td>-0.28</td>
<td>-0.37</td>
</tr>
<tr>
<td>GRL</td>
<td>0.063</td>
<td>-0.02</td>
<td>-0.083</td>
<td>0.095</td>
<td>-0.039</td>
<td>-0.13</td>
</tr>
<tr>
<td>MED</td>
<td>0.18</td>
<td>-0.2</td>
<td>-0.39</td>
<td>0.15</td>
<td>-0.17</td>
<td>-0.32</td>
</tr>
<tr>
<td>NEU</td>
<td>0.14</td>
<td>-0.19</td>
<td>-0.33</td>
<td>0.086</td>
<td>-0.27</td>
<td>-0.36</td>
</tr>
<tr>
<td>WAF</td>
<td>0.23</td>
<td>-0.24</td>
<td>-0.47</td>
<td>0.21</td>
<td>-0.23</td>
<td>-0.44</td>
</tr>
<tr>
<td>EAF</td>
<td>0.15</td>
<td>-0.38</td>
<td>-0.53</td>
<td>0.24</td>
<td>-0.076</td>
<td>-0.32</td>
</tr>
<tr>
<td>SAF</td>
<td>0.28</td>
<td>-0.27</td>
<td>-0.54</td>
<td>0.29</td>
<td>-0.27</td>
<td>-0.57</td>
</tr>
<tr>
<td>SAH</td>
<td>0.22</td>
<td>-0.24</td>
<td>-0.46</td>
<td>0.27</td>
<td>-0.32</td>
<td>-0.6</td>
</tr>
<tr>
<td>SEA</td>
<td>0.23</td>
<td>-0.3</td>
<td>-0.54</td>
<td>0.22</td>
<td>-0.16</td>
<td>-0.39</td>
</tr>
<tr>
<td>EAS</td>
<td>0.052</td>
<td>-0.11</td>
<td>-0.16</td>
<td>0.11</td>
<td>-0.25</td>
<td>-0.36</td>
</tr>
<tr>
<td>SAS</td>
<td>0.31</td>
<td>-0.2</td>
<td>-0.51</td>
<td>0.19</td>
<td>-0.21</td>
<td>-0.39</td>
</tr>
<tr>
<td>CAS</td>
<td>0.12</td>
<td>-0.29</td>
<td>-0.42</td>
<td>0.13</td>
<td>-0.23</td>
<td>-0.36</td>
</tr>
<tr>
<td>TIB</td>
<td>0.084</td>
<td>-0.1</td>
<td>-0.19</td>
<td>0.087</td>
<td>-0.075</td>
<td>-0.16</td>
</tr>
<tr>
<td>NAS</td>
<td>0.2</td>
<td>-0.016</td>
<td>-0.21</td>
<td>-0.035</td>
<td>-0.24</td>
<td>-0.2</td>
</tr>
</tbody>
</table>
Table A.10: Comparison of synthetic and empirical distribution functions for seasonal average precipitation at three degrees warming, JJA / SON

<table>
<thead>
<tr>
<th>Region</th>
<th>JJA</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\delta F_{0.05}$</td>
<td>$\delta F_{0.95}$</td>
<td>$\delta F_{0.95-0.05}$</td>
<td>$\delta F_{0.05}$</td>
<td>$\delta F_{0.95}$</td>
<td>$\delta F_{0.95-0.05}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NAU</td>
<td>0.2</td>
<td>-0.11</td>
<td>-0.31</td>
<td>0.24</td>
<td>-0.28</td>
<td>-0.52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAU</td>
<td>0.14</td>
<td>-0.1</td>
<td>-0.25</td>
<td>0.24</td>
<td>-0.22</td>
<td>-0.45</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AMZ</td>
<td>0.14</td>
<td>-0.096</td>
<td>-0.24</td>
<td>-0.01</td>
<td>0.018</td>
<td>0.028</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SSA</td>
<td>0.14</td>
<td>-0.22</td>
<td>-0.37</td>
<td>0.067</td>
<td>-0.16</td>
<td>-0.22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAM</td>
<td>0.13</td>
<td>-0.25</td>
<td>-0.38</td>
<td>4e-04</td>
<td>-0.16</td>
<td>-0.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WNA</td>
<td>0.16</td>
<td>-0.25</td>
<td>-0.41</td>
<td>0.19</td>
<td>-0.12</td>
<td>-0.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNA</td>
<td>0.017</td>
<td>-0.18</td>
<td>-0.2</td>
<td>0.11</td>
<td>-0.27</td>
<td>-0.38</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ENA</td>
<td>0.024</td>
<td>-0.31</td>
<td>-0.33</td>
<td>0.13</td>
<td>-0.21</td>
<td>-0.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GRL</td>
<td>0.053</td>
<td>-0.27</td>
<td>-0.33</td>
<td>0.12</td>
<td>-0.16</td>
<td>-0.28</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MED</td>
<td>0.15</td>
<td>-0.21</td>
<td>-0.37</td>
<td>0.16</td>
<td>-0.17</td>
<td>-0.33</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NEU</td>
<td>-0.0068</td>
<td>-0.11</td>
<td>-0.1</td>
<td>0.056</td>
<td>-0.17</td>
<td>-0.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>WAF</td>
<td>0.064</td>
<td>-0.12</td>
<td>-0.18</td>
<td>0.063</td>
<td>-0.22</td>
<td>-0.28</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EAF</td>
<td>0.24</td>
<td>-0.19</td>
<td>-0.43</td>
<td>0.078</td>
<td>0.044</td>
<td>-0.034</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAF</td>
<td>0.26</td>
<td>-0.24</td>
<td>-0.5</td>
<td>0.23</td>
<td>-0.18</td>
<td>-0.41</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAH</td>
<td>0.2</td>
<td>-0.35</td>
<td>-0.54</td>
<td>0.2</td>
<td>-0.27</td>
<td>-0.47</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SEA</td>
<td>0.16</td>
<td>-0.13</td>
<td>-0.3</td>
<td>0.16</td>
<td>-0.042</td>
<td>-0.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EAS</td>
<td>0.18</td>
<td>-0.23</td>
<td>-0.41</td>
<td>0.042</td>
<td>-0.14</td>
<td>-0.18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAS</td>
<td>0.19</td>
<td>-0.37</td>
<td>-0.57</td>
<td>0.037</td>
<td>-0.24</td>
<td>-0.28</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAS</td>
<td>0.23</td>
<td>-0.19</td>
<td>-0.42</td>
<td>0.13</td>
<td>-0.14</td>
<td>-0.27</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TIB</td>
<td>0.046</td>
<td>-0.12</td>
<td>-0.16</td>
<td>0.21</td>
<td>-0.16</td>
<td>-0.38</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NAS</td>
<td>0.033</td>
<td>-0.18</td>
<td>-0.21</td>
<td>0.082</td>
<td>-0.13</td>
<td>-0.21</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure A.7: Regional Temperature Distributions at 2 and 3 Degrees Warming, Western Hemisphere- December, January, February
Figure A.8: Regional Temperature Distributions at 2 and 3 Degrees Warming, Western Hemisphere - March, April, May
Figure A.9: Regional Temperature Distributions at 2 and 3 Degrees Warming, Western Hemisphere - June, July, August
Figure A.10: Regional Temperature Distributions at 2 and 3 Degrees Warming, Western Hemisphere - June, July, August
Figure A.11: Regional Temperature Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere- December, January, February
Figure A.12: Regional Temperature Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - March, April, May
Figure A.13: Regional Temperature Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - June, July, August
Figure A.14: Regional Temperature Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - June, July, August
Figure A.15: Regional Precipitation Distributions at 2 and 3 Degrees Warming, Western Hemisphere - December, January, February
Figure A.16: Regional Precipitation Distributions at 2 and 3 Degrees Warming, Western Hemisphere - March, April, May
Figure A.17: Regional Precipitation Distributions at 2 and 3 Degrees Warming, Western Hemisphere - June, July, August
Figure A.18: Regional Precipitation Distributions at 2 and 3 Degrees Warming, Western Hemisphere - September, October, November
Figure A.19: Regional Precipitation Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere- December, January, February
Figure A.20: Regional Precipitation Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - March, April, May
Figure A.21: Regional Precipitation Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - June, July, August
Figure A.22: Regional Precipitation Distributions at 2 and 3 Degrees Warming, Eastern Hemisphere - September, October, November
Figure A.23: Regional Boundaries adopted from Giorgi and Mearns (2002)
Figure A.24: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming - December, January, February
Figure A.25: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming - December, January, February
Figure A.26: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 2°C Warming - March, April, May
Figure A.27: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming - March, April, May
Figure A.28: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming - June, July, August
Figure A.29: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming - June, July, August
Figure A.30: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming - September/October/December
Figure A.31: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2°C Warming - September/October/December
Figure A.32: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 3° Warming - December, January, February
Figure A.33: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3° Warming - December, January, February
Figure A.34: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 3° Warming - March, April, May
Figure A.35: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3° Warming - March, April, May
Figure A.36: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 3° Warming - June, July, August
Figure A.37: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3° Warming - June, July, August
Figure A.38: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Western Hemisphere at 3°C Warming - September/October/December
Figure A.39: Regional Distributions of Synthetic Temperature Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3° Warming - September/October/December
Figure A.40: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming - December, January, February
Figure A.41: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming - December, January, February
Figure A.42: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming- March, April, May
Figure A.43: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at $2^\circ$ Warming- March, April, May
Figure A.44: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming - June, July, August
Figure A.45: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming - June, July, August
Figure A.46: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 2° Warming - September/October/December
Figure A.47: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 2° Warming - September/October/December
Figure A.48: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at 3° Warming- December, January, February
Figure A.49: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3°C Warming - December, January, February.
Figure A.50: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at $3^\circ$ Warming - March, April, May
Figure A.51: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3° Warming- March, April, May
Figure A.52: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at $3^\circ$ Warming- June, July, August
Figure A.53: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at 3° Warming - June, July, August
Figure A.54: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Western Hemisphere at $3^\circ$ Warming - September/October/December
Figure A.55: Regional Distributions of Synthetic Precipitation Change compared to Histograms of Modeled Change in the Eastern Hemisphere at $3^\circ$ Warming - September/October/December
Appendix B

Yield Response Surface Results

B.1 Results

The response for non-irrigated corn to early season growing degree days is given in 3.1. Log yields for corn show a strong increase up to approximately 750 growing degree days. This is followed by a gradual decrease to around 1500 degree days, followed by a more rapid decline afterwards. Looking at the baseline exposure it is clear that the bulk of the distribution is centered towards the decreasing and negative portion of the log yield response. For both the two and three degree distributions there is a shift towards higher exposure to growing degree days, with both histograms showing the highest density around 2250. The response for non-irrigated corn to late season growing degree days is given in 3.2. Log yields increase rapidly up to 500 growing degree days and then remain essentially flat until around 2000 growing degree days where they experience a decline and become negative. Unlike the early season we see that the baseline climate distribution aligns well with the optimal exposure between about 500 and 2000 late season growing degree days, with very little exposure beyond 2000 growing degree days. However, looking at the distributions for exposure at 2 and 3 degrees there is a notable shift towards higher exposure, in particular at 3 degrees. This suggests the chance for substantial negative impacts on corn yields. The response to early and late season precipitation is given in figures 3.3 and 3.4 respectively. Log yield response to early season precipitation is similar to that of early season growing degree days. Log yield peaks at 350 mm and slowly falls off until around 1250 mm. Beyond 1250 mm yield suffers, however confidence in these estimates decreases. Log yield appears fairly invariant to late season precipitation. Levels above 1000 mm may introduce slight benefits, however uncertainty in these estimates is high. Baseline precipitation values fall just slightly below the ideal response range. Both warming distributions show a slight tendency towards high
levels of precipitation which would potentially lead to a slight decrease in yield.

The log yield response to early season growing degree days for soybeans is given in figure B.1. Log yield values reach their peak at around 600 early season growing degree days before decreasing and becoming negative around 1700 growing degree days. Similar to sorghum there’s a higher degree of certainty in the estimates for growing degree days above the maximum, due to the sample data distribution. The baseline histogram suggests that the majority of exposure occurs along the negative portion of the response curve. Both the 2 and 3 degree warming scenario show a slight shift towards higher GDD exposure, suggesting a potential for strong decrease in yields. Late season growing degree day are given in figure B.2. There is an overall linear impact on yield, with peak yields occurring at 2000 late season growing degree days. The lower and upper tail of the response curve show a higher degree of certainty than the tails. The bulk of the baseline histograms aligns with the positive portion of the log yield response. At both 2 and 3 degree warming the distribution is strongly shifted towards higher level of exposure which suggest beneficial effects on log yield. Precipitation effects are given in figures B.3 and B.4 respectively. Log yield response to early season precipitation peaks at 500 mm and remains fairly invariant at higher levels of heat accumulation. Late season precipitation shows a fairly invariant response with a slight increase towards the tail end of the sample distribution, accompanied by an increase in uncertainty. In both cases the baseline precipitation are aligned with an optimal portion of the log yield response, and the warming scenarios show a slight tendency towards higher precipitation.

The log yield response for rice to early growing degree days is given in figure B.5. Unlike other crops in this study, rice yields are fairly constant across each of the predictor variables once a given threshold of heat accumulation is reached. For the early season this occurs at around 1250 growing degree days, after which the response remains stable. The baseline exposure is aligned with the linear portion of the response curve, suggesting that current growing conditions are ideal. While both warming scenarios show higher exposure, there is
no indication that this would be harmful given the linearity of the response curve at high
temperatures. Late season growing degree days exposure is given in B.6. Optimal yield
conditions occur above 500 growing degree days. Additionally the confidence intervals on
the estimates are extremely tight. Response to precipitation is given in figures B.7 and B.6.
Rice appears to be completely invariant to changes in precipitation across early and late
seasons.

The log yield response for millet to early season growing degree days is given in figure
B.9. Early season log yield values peak around 500 growing degree days. There is a sharp
increase in initial early season heat accumulation followed by a more gradual decrease.
Detrimental heat levels occur around 1750 growing degree days. The sample distribution is
sparse around the peak response, resulting in quite a bit of uncertainty at the lower range
of the sample, and perhaps suggesting that millet was not grown under ideal conditions.
Both warming distributions are wider than the baseline, with a slight increase in exposure
to high levels of GDD. The response to late season growing degree days is given in B.10.
During the late season log yield values peak near 2000 growing days. Positive values of log
yield are seen only above 1500 growing degree days, indicating that the crop grows best
under high levels of late season heat accumulation. Exposure under warming conditions
shows the potential of lower performance than the baseline, however log yields still remain
positive. The response to early and late season precipitation is given in figures B.11 and
B.12. For early season precipitation the log yield peaks around 400 mm and remains
fairly invariant to changes above that. A slight drop occurs towards the end of the sample
distribution, but uncertainty in this estimate is fairly high. Warming scenarios show a
higher likelihood of increased precipitation, however this should have no effect on log yield.
For late season precipitation the log yield response is nearly zero across the majority of
the sample distribution, indicating that late season precipitation has only a small effect
on yield. Again, the warming exposure suggests a higher likelihood of increased levels of
precipitation.
The log yield response for sorghum to early season growing degree days is given in figure B.13. Log yield values reach their peak at around 800 early season growing degree days. Log yields are positive between 400 and 1800 early season growing degree days, and negative outside of that range. The majority of the sample input data are distributed to the right of the log yield maximum, leading to a decrease in uncertainty in the higher values of growing degree days, as well as suboptimal growing conditions. At 2 degrees warming the distribution is more uniform, with a slight increased likelihood of higher exposure. At 3 degrees warming the increased warming is even more likely. Late season response to growing degree days are reported in figure B.14 and show a steady increasing trend, peaking at 2000 growing degree days and dropping off thereafter. Baseline exposure is aligned mostly along the positive log yield response, with highest exposure occurring along the maximum. At 2 and 3 degrees warming the distribution is much more spread out, suggesting a decrease in yield at both ends of the response curve. Log yield response to precipitation is given in figures B.15 and B.16. Log yield response to early season precipitation indicates an optimum response at 500 mm of rainfall, which aligns well with the baseline exposure. Increased rainfall from the optimum slowly decreases log yield, with negative log yields occurring above 750 mm. Both the 2 and 3 degree exposure histograms suggest higher levels of precipitation along the decreasing portions of the log yield response curve. Log yield is invariant to late season precipitation, with a slight increase after 750 mm.

The response for non-irrigated beans is given in figure B.21. Log yields for beans show a strong peak at approximately 500 early season growing degree days. There is a rapid improvement in yield between 0 and 500 degree days followed by a more gradual decline. Late season growing degree days show an overall positive trend, though there appears to be a noticeable peak occurring at approximately 400 late season growing degree days, followed by a slight decline. The decline levels at around 750 growing degree days and then stays fairly stable with a slight increase. The slight increase could potentially be attributed to seasons that saw both a high level of late season heat as well as precipitation. There is a
strong degree of confidence in the growing degree relationships, particularly with higher level of heat accumulations. For precipitation there is a strong peak at 500 mm of cumulative early season precipitation, followed by a moderate decline. Model confidence decreases significantly as early cumulative precipitation increases. This may be potentially linked to temperature effects, and the combination of both warm and cool early seasons accompanied by higher levels of precipitation. Log yield remains fairly invariant to changes in late season precipitation, however confidence is lower again at the higher levels.

The log yield response for potatoes is given in figure B.17. Early season log yield values quickly peak around 500 growing degree days. Log yield becomes negative below approximately 250 growing degree days and 1500 growing degree days. Baseline values of exposure occur above the optimal levels. At 2 and 3 degrees there is a slight chance of increased exposure, however the overall mass of the density remains similar to the baseline. Late season growing degree day response is given in B.18. The ideal range of late season growing degree days occurs above 1500 degree days. The warming histograms suggest a positive impact to yields at both 2 and 3 degree warming. Early season precipitation has a large degree of impact on log yields with maximum yields occurring above 500 mm and remaining fairly constant. Log yield response to early and late season precipitation is given in figures B.19 and ?? . Negative log yield occurs below about 250 mm of precipitation. Log yield is fairly invariant to changes in late season precipitation. Above 1000 mm there appears to be an increase in log yield, however this extends well into the tails of the sample distribution so there is a large degree of uncertainty.

The log yield response for beets is given in figure B.22. Early season log yields peak at approximately 1000 growing degree days. There is a fairly rapid increase in log yield between 0 and 1000 growing degree days followed by a subtle decrease. During the late season log yield shows a fairly cubic relationship to growing degree days, with decreases in yield for growing degree days less than 600, and increases over 1500. The raw yield data are mostly distributed between 500 and 1500 growing degree days, so values outside of
this range show lower confidence. Higher levels of early season precipitation seem to have a strong effect on yield, with positive log yield values starting above 250 mm. Notably the majority of the early season precipitation values are distributed between 0 and 700 mm, giving a high degree of confidence in estimates at the lower range. Beyond 500 mm the uncertainty bounds grow substantially. Late season precipitation appears less crucial, however values below 250 show a negative impact on yields. Confidence in the estimates drops beyond about 600 mm as the data are distributed towards the lower ranges.

The log yield response for oats is given in figure B.23. Early season log yield values peak around 500 growing degree days. Early season growing degree days have the largest impact on yield. Beyond 1500 early season growing degree days result in negative log yield values. Late season growing degree days show a peak at approximately 1750 growing degree days. Log yields become negative below 1500 late season growing degree days, however they are positive below 500 growing degree days with a higher degree of uncertainty. Above 1750 growing degree days the response remains stable. Log yield responds quickly to early season precipitation, with a peak around 500 mm and a stable response thereafter. Late season precipitation appears to have a negligible effect until around 750 mm where a slight increase in yield is seen. There are limited data points in the upper end of the sample so this increase is subject to a higher degree of uncertainty.

The log yield response for winter wheat is given in figure B.24. Log yield values are negative at the lower tail end of the sample distribution up to 1000 growing degree days. Log yield reaches a peak at approximately 1500 early season growing degree days before quickly becoming negative again. The response appears to again increase above 2250 growing degree days, however the uncertainty also increases as this reaches the upper tail end of the sample distribution. Late season response reaches a peak at 1250 growing degree days. The uncertainty in the estimate is lowest to the right of the log yield maximum. Early season precipitation has a minimal effect on log yield across the majority of the sample distribution, and shows a decrease in log yield towards the upper end of the sample distribution beyond
Late season precipitation shows a slightly negative trend across the majority of the sample distribution.

### B.1.1 Irrigated Yield Response

The log yield response for corn to early season growing degree days is given in figure ???. Early season log yield reaches a peak at 1700 growing degree days and remains constant above that value. Baseline exposure is concentrated along the linear and optimal portion of the yield response surface. Though higher exposure occurs at 2 and 3 degrees warming, there is minimal effect on yields. The log yield response for corn to late season growing degree days is given in figure ???. The log yield response for corn to precipitation is given in figures ?? and ???. For late season log yield the peak occurs at 500 growing degree days and remains stable. Early season precipitation has a slightly negative effect on log yields beyond 500 growing degree days. Late season precipitation has no effect. Irrigated corn reaches a yield peak at a higher early season heat accumulation than irrigated, at a level that is above optimum for non-irrigated varieties.

The log yield response for soybeans to early season growing degree days is given in figure B.25. Early season log yield peaks at nearly 2000 growing degree days and remains constant at higher values. Baseline and warming exposure aligns with the optimal portion of the log yield response curve. The log yield response for soybeans to late season growing degree days is given in figure B.26. Late season log yield peaks at 500 growing degree days and remains constant at higher values. Baseline and warming exposure aligns with the optimal portion of the log yield response curve. The effects of early and late season precipitation are given in figures B.27 and B.26. Both early and late season precipitation has no effect on log yield. The early season optimum heat accumulation for the irrigated variety of soybean would have negative effects on the non-irrigated variety. However, the late season optimum for the non-irrigated variety occurs at a higher level than the irrigated.5

The log yield response for rice to early season growing degree days is given in figure
For the early season peak log yield occurs at around 500 growing degree days and remains linear above that value. The log yield response for rice to late season growing degree days is given in figure B.30. Similar to the early season, peak log yield for late season exposure occurs at around 500 growing degree days and remains linear above that value. The effects of early and late season precipitation are given in figures B.31 and B.30. Log yield is invariant to both early and late season precipitation along the entirety of the sample distribution. Irrigated and non-irrigated rice varieties perform identically given the model constructs used to simulate them.

The log yield response for millet to early season growing degree days is given in figure B.33. Early season log yield reaches a peak at roughly 500 growing degree days and remains constant above that value. The same pattern holds for late season growing degree days, shown in figure B.34. Early and late season precipitation responses are given in figures B.35 and B.36 and show no effect on yield. Compared to non-irrigated millet the irrigated variety reaches an optimum at a lower level of growing degree days, but shows no detriment from heat accumulation above the optimum. Notably, the late season optimum heat accumulation occurs much later in the non-irrigated variety than in the irrigated variety.

The log yield response for sorghum to early growing degree days is given in figure B.37. Early season log yield peaks at 1000 growing degree days and drops slightly above 1750 growing degree days. At 2 and 3 degree warming there is an increased likelihood of exposure to more than 1750 growing degree days, indicating the potential for losses. The log yield response for sorghum to late growing degree days is given in figure B.38. Late season response peaks just above 500 growing degree days and remains constant before dropping off at 2000 growing degree days. Both warming histograms show an increased likelihood of exposure above this threshold. Early and late season precipitation responses are given in figures B.39 and B.40. There is a notable negative response to increasing early season precipitation above 500 mm, and no notable effect of late season precipitation. The early season irrigated optimum aligns with the non-irrigated optimum, however the non-irrigated
late season optimum occurs at a much higher temperature than the irrigated variety. Under the warming scenarios there’s a higher likelihood of high levels of precipitation which could lead to yield loss.

The log yield response for potatoes to early season growing degree days is given in figure B.41. Early season log yield response peaks at 1000 growing degree days and remains constant for higher levels. The log yield response for potatoes to late season growing degree days is given in figure B.42. Late season log yield response peaks at 500 degree days and remains constant for higher levels. Early and late season precipitation responses are given in figures B.43 and B.44. Early season response to precipitation is invariant below 1000 mm, and shows a slight negative trend at higher levels. Late season log yield is invariant to precipitation across the entire sample distribution. Non irrigated potato yield response peaks at a lower level of early season growing degree days and a higher level of late season growing degree days.

The log yield response for beans is given in figure B.45. Log yield reaches a peak at the maximum of the early season growing degree day distribution, at roughly 2200 growing degree days. There appears to be no detrimental impacts from high levels of early season heat accumulation. For the late season the log yield maximum occurs around 500 growing degree days and remains invariant above that value. Both early and late season precipitatin have no noticeable affect on yield. In contrast to the non-irrigated beans, the irrigated beans thrive under much warmer early season conditions, and show a qualitatively similar relationship to late season growing degree days.

The log yield response for beets is given in figure B.46. Early season log yield reaches a peak at 1000 growing degree days and remains fairly invariant above that value. Late season log yield peaks at 500 growing degrees and remains stable across the sample distribution. Both early and late season precipitation have no discernible impact on yields across the sample distribution. In contrast, non-irrigated beet yield is strongly impacted by early season precipitation, with a clear optimum occurring after 500 mm. Both the irrigated
and non irrigated varieties have similar early season growing degree day peaks, however the irrigated shows no detrimental effects to higher heat accumulations.

The log yield response for oats is given in figure B.47. Early and late season log yield responses reach a peak at 500 growing degree days and remain constant for values above that. Early season log yield response to precipitation shows a slight negative trend, with values above 700 mm leading to a negative log yield. The early and late season optimum growing degree days align with the non-irrigated varieties, however there is no detriment to higher degrees of heat accumulation.

The log yield response for winter wheat is given in figure B.48. Early season and late season log yield peaks at approximately 1250 growing degree days. Log yield is invariant to changes in both early and late season precipitation. The irrigated and non irrigated varieties both peak at similar levels of growing degree days, however the irrigated variety shows no decrease beyond the optimum levels.
Figure B.1: Non-Irrigated Yield Response: Soybean Early Growing Degree Days
Figure B.2: Non-Irrigated Yield Response: Soybean Late Growing Degree Days
Figure B.3: Non-Irrigated Yield Response: Soybean Early Precipitation
Figure B.4: Non-Irrigated Yield Response: Soybean Late Precipitation
Figure B.5: Non-Irrigated Yield Response: Rice Early Growing Degree Days
Figure B.6: Non-Irrigated Yield Response: Rice Late Growing Degree Days

The figure illustrates the non-irrigated yield response of rice over late growing degree days (GDD). The x-axis represents the baseline, 2-degree, and 3-degree GDD scenarios, while the y-axis represents the log yield response. The data shows a trend where yield response generally increases with an increase in GDD, with more pronounced changes observed in the 2-degree and 3-degree scenarios compared to the baseline. The shaded area represents the confidence interval for the yield response.
Figure B.7: Non-Irrigated Yield Response: Rice Early Precipitation

![Diagram showing the relationship between log yield response and early season precipitation for different scenarios: Baseline, 2 Degree, and 3 Degree.]
Figure B.8: Non-Irrigated Yield Response: Rice Late Precipitation
Figure B.9: Non-Irrigated Yield Response: Millet Early Growing Degree Days
Figure B.10: Non-Irrigated Yield Response: Millet Late Growing Degree Days
Figure B.11: Non-Irrigated Yield Response: Millet Early Precipitation
Figure B.12: Non-Irrigated Yield Response: Millet Late Precipitation
Figure B.13: Non-Irrigated Yield Response: Sorghum Early Growing Degree Days
Figure B.14: Non-Irrigated Yield Response: Sorghum Late Growing Degree Days
Figure B.15: Non-Irrigated Yield Response: Sorghum Early Precipitation
Figure B.16: Non-Irrigated Yield Response: Sorghum Late Precipitation
Figure B.17: Non-Irrigated Yield Response: Potato Early Growing Degree Days
Figure B.18: Non-Irrigated Yield Response: Potato Late Growing Degree Days
Figure B.19: Non-Irrigated Yield Response: Potato Early Precipitation
Figure B.20: Non-Irrigated Yield Response: Potato Late Precipitation

Late Season Precipitation

Log Yield Response

Baseline,
2 Degree,
3 Degree

0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0000
0.0005
0.0010
0.0015
0.0020
0.0000
0.0005
0.0010
0.0015
0.0020
0.0000
0.0005
0.0010
0.0015
0.0020

0 500 1000 1500

0.0000
0.0005
0.0010
0.0015
0.0020
0.0025
0.0000
0.0005
0.0010
0.0015
0.0020
Figure B.21: Non-Irrigated Yield Response: Beans
Figure B.22: Non-Irrigated Yield Response: Beets
Figure B.23: Non-Irrigated Yield Response: Oats
Figure B.24: Non-Irrigated Yield Response: Winter Wheat
Figure B.25: Irrigated Yield Response: Soybean Early Growing Degree Days
Figure B.26: Irrigated Yield Response: Soybean Late Growing Degree Days
Figure B.27: Irrigated Yield Response: Soybean Early Precipitation
Figure B.28: Irrigated Yield Response: Soybean Late Precipitation
Figure B.29: Irrigated Yield Response: Rice Early Growing Degree Days
Figure B.30: Irrigated Yield Response: Rice Late Growing Degree Days
Figure B.31: Irrigated Yield Response: Rice Early Precipitation
Figure B.32: Irrigated Yield Response: Rice Late Precipitation
Figure B.33: Irrigated Yield Response: Millet Early Growing Degree Days
Figure B.34: Irrigated Yield Response: Millet Late Growing Degree Days
Figure B.35: Irrigated Yield Response: Millet Early Precipitation
Figure B.36: Irrigated Yield Response: Millet Late Precipitation
Figure B.37: Irrigated Yield Response: Sorghum Early Growing Degree Days

The diagram illustrates the log yield response to early season growing degree days for sorghum. The plot compares the baseline yield response (red line) and the impact of 2 and 3 degree increases in growing degree days.

- **Baseline Yield Response**: The red line represents the baseline yield response without any growing degree day adjustments.
- **2 Degree Impact**: The orange bar graph shows the yield response with a 2 degree increase in growing degree days. The bars indicate a small increase in yield response compared to the baseline.
- **3 Degree Impact**: The red bar graph illustrates the yield response with a 3 degree increase in growing degree days. The bars show a more pronounced increase in yield response compared to the 2 degree scenario.

The y-axis represents the log yield response, while the x-axis represents the early season growing degree days. The scale on the y-axis ranges from -2.0 to 0.5, with intermediate values indicating the level of yield response. The x-axis ranges from 0 to 2500 growing degree days, with increments of 500 for clarity.
Figure B.38: Irrigated Yield Response: Sorghum Late Growing Degree Days

The figure shows the relationship between late season growing degree days and log yield response for sorghum. The x-axis represents the late season growing degree days, while the y-axis shows the log yield response. The graph includes baseline and 2-degree and 3-degree scenarios, with each showing a different response pattern. The baseline scenario is represented by a solid red line, while the 2-degree and 3-degree scenarios are shown with shaded areas.

- **Baseline**:
  - The baseline shows a gradual increase in log yield response as late season growing degree days increase.
  - The baseline remains relatively flat with slight fluctuations.

- **2-Degree**:
  - The 2-degree scenario shows a more pronounced increase in log yield response compared to the baseline.
  - There is a notable upward trend with a peak around 1500 growing degree days.
  - After the peak, the response decreases but remains above the baseline.

- **3-Degree**:
  - The 3-degree scenario indicates an even more significant increase in log yield response.
  - There is a sharp rise with a peak around 1500 growing degree days, followed by a steeper decline.
  - The response remains above the 2-degree scenario throughout.

The figure illustrates how irrigation impacts yield in sorghum, with different scenarios showing varying degrees of response to late season growing degree days.
Figure B.39: Irrigated Yield Response: Sorghum Early Precipitation
Figure B.40: Irrigated Yield Response: Sorghum Late Precipitation
Figure B.41: Irrigated Yield Response: Potato Early Growing Degree Days
Figure B.42: Irrigated Yield Response: Potato Late Growing Degree Days
Figure B.43: Irrigated Yield Response: Potato Early Precipitation
Figure B.44: Irrigated Yield Response: Potato Late Precipitation
Figure B.45: Irrigated Yield Response: Beans
Figure B.46: Irrigated Yield Response: Beets
Figure B.47: Irrigated Yield Response: Oats
Figure B.48: Irrigated Yield Response: Winter Wheat
Bibliography


Curriculum Vitae

Jordan R. Winkler 1354 Scrub Oak Circle Boulder, CO 80305

Education
B.S., Chemical Engineering, Clarkson University, 2005

Professional Experience

- 2014 - Present: Technical Director, Living Green Network
- 2013 - Present: Visiting Scientist, Institute for Mathematics Applied to Geosciences, National Center for Atmospheric Research
- 2013 : Research Assistant, Department of Earth and Environment, Boston University
- 2012 : Visiting Scientist, Institute for Mathematics Applied to Geosciences, National Center for Atmospheric Research
- 2007-2012 : Teaching Fellow, Department of Earth and Environment, Boston University
- 2011: Lecturer, Department of Earth and Environment, Boston University
- 2010: Consultant, Red Cross Red Crescent Climate Centre
- 2008: Graduate Research Fellow, Frederick S. Pardee Center for the Study of the Longer Range Future, Boston University
- 2008 : Research Assistant, Global Development and Environment Institute, Tufts University
- 2007: Research Assistant, Stockholm Environmental Institute, Boston
• 2006 - 2007: Research Assistant, Department of Geography, Boston University

Publications: