Climate, Agriculture and Food

Submitted as a chapter to the *Handbook of Agricultural Economics*

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Abstract

Agriculture is arguably the most climate-sensitive sector of the economy. Growing concerns about anthropogenic climate change have increased research interest in assessing its potential impact on the sector and in identifying policies and adaptation strategies to help the sector cope with a changing climate. This chapter provides an overview of recent advancements in the analysis of climate change impacts and adaptation in agriculture with an emphasis on methods. The chapter provides an overview of recent research efforts addressing key conceptual and empirical challenges. The chapter also discusses practical matters about conducting research in this area and provides reproducible R code to perform common tasks of data preparation and model estimation in this literature. The chapter provides a hands-on introduction to new researchers in this area.

Keywords: climate change; impacts; adaptation; agriculture.

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1 Introduction

Climate has always been critical to the development of agriculture. For instance, changes in climate are believed to have played an important role in the origin of agriculture (Gupta, 2004; Matranga, 2017). More recently, the story surrounding the territorial expansion of agriculture over the past few centuries was also one about adapting farming practices and existing crops to new climates (e.g. Olmstead and Rhode, 2011).

But climate is now changing at an unprecedented rate overwhelmingly due to human causes (Pachauri et al., 2014). And even as the extent of global agricultural land stabilizes, and agricultural productivity continues to rise, climatic shocks continue to play a central role in explaining fluctuations in agricultural production (Lesk et al., 2016). In fact, recent climate change appears to have already substantially slowed down global agricultural productivity growth (Ortiz-Bobea et al., 2021). In this context, research is needed not only to understand potential future impacts of anthropogenic climate change on agriculture, but also to identify efficient strategies to enhance adaptation to a changing climate. This includes identifying market failures and possible barriers to adaptation.

Unlike mitigation of climate change, which requires a coordinated international effort to reduce greenhouse emissions, adaption is generally framed as a local matter, something that only local private agents have to deal with. However, farmers rely directly or indirectly on public infrastructure, and buy technologies and sell products in markets with important government presence and regulation. Moreover, the increasing globalization of agricultural markets and technologies challenge this view. So agricultural adaptation to climate change goes beyond the boundaries of the farm.

This chapter is primarily aimed to introduce new researchers to the analysis of climate change impacts on the agricultural sector. Most of the content should be highly accessible but familiarity with matrix algebra is necessary to take fully advantage of the content. Importantly, the chapter provides code and data to reproduce common tasks while conducting research in this area, including data preparation and cleaning as well as the estimation of semi-parametric models. All of the figures illustrating these techniques are fully reproducible in R. R is a an increasingly popular open source statistical software that will ensure a wide access to this material to all researchers.

The chapter is organized in 3 main sections. Section 2 covers important basic concepts and terminology regarding climate change and agriculture and discusses various aspects regarding common datasets used in economic analysis in the field. Subsection 2.1 defines weather as a random variable and climate as describing the moments of the underlying distribution of that weather variable. Weather change and climate change mean different
things and this clarification will allow a more precise discussion surrounding these concepts throughout the chapter. Subsection 2.2 defines what we mean by adaptation to climate change following the formal definition adopted by the Intergovernmental Panel of Climate Change (IPCC).

Conducting research in this area also require familiarity with different types of weather data. Subsection 2.3 discusses important features about historical weather datasets including their format (e.g. gridded, weather stations). I also provide the names of common datasets used in the literature. Subsection 2.4 also discusses the basics of General Circulation Models (GCM) and how the climate science community improves these models over time within global inter-comparison projects that feed into the IPCC reports. Subsection 2.5 covers some basic concepts regarding the use and interpretation of degree days. As it will become apparent, temperature has been found to be a critical driver of agricultural production. The use of degree days is not new in agriculture science, and I provide a historical perspective on the concept and how its use has evolved in the more recent economic literature.

Section 3 dives into specific areas of research or methodologies to assess the economic impacts of extreme weather or climate change on agriculture. An important emphasis in some of the techniques and approaches presented in this section deal with the extent to which farmer adaptations are captured and represented. Subsection 3.1 provides an overview of process-based biophysical approach of modeling crop yields and how these are integrated into economic models to simulate climate change impacts to the agricultural sector. That presentation provides an overview of the early literature as well as recent trends toward the adoption of multi-model ensembles and inter-comparison projects.

Subsection 3.2 transitions to discuss the cross-sectional Ricardian approach, one of the first econometric approaches introduced to evaluate the impact of climate change on agriculture. Here I discuss some the advantages and pitfalls of this approach including recent advances. The following subsection 3.3 deals with models estimating the effects of weather fluctuations on agricultural profits or aggregate measures of productivity based on panel data. Because these models include location fixed effects, they provide a more credible identification of the effect of weather than correctional approaches. I also provide an overview of their limitations.

Subsection 3.4 discusses the rise of statistical crop yield models in agricultural economics and related fields. These models are also based on panel data but their focus on specific crop yields allows researchers to engage in more detailed crop-specific treatment of weather variables. I try to provide a historical perspective of the origin of these models before the renewed interest in the context of climate change. I also briefly discuss new creative ways to combine statistical and biophysical approaches to modeling crop yields in subsection 3.5.
These new efforts provide exciting new frontiers of collaboration with natural scientists.

In subsection 3.6 I discuss an emerging area of research proposing new methods to overcome certain perceived limitations of both cross-sectional and panel approaches. I describe these recent advances and their limitations. I highlight new work that clarifies the theoretical interpretation of panel estimates. I also provide a brief overview to retrospective climate change studies in subsection 3.7. Most of the research emphasis has focused on assessing future potential impacts of climate change on the sector. However, anthropogenic forces have already changed climate which is about 1°C warmer than in pre-industrial times. As climate continues to change, such retrospective studies are likely to increase in popularity. I provide a brief overview of early and more recent studies. The rest of section 3 is less about methods, and more about various aspects of capturing climate change impacts and farmer and market responses.

There is a vast literature assessing impacts on crop yields, but there is much less work focusing on the impact on crop quality. Subsection 3.8 presents recent work on this topic and lays out some challenges for future work. Subsection 3.9 discusses the analysis of planting and harvesting decisions, ranging from the timing of planting, to the decision to increase cropping frequency (e.g. double cropping). Naturally, irrigation is central to agriculture and is often perceived as an important mechanism for farmers to adapt a water scarcity in a changing climate. I cover this topic in subsection 3.10, where I discuss early studies but also provide a look to more recent work based on new data sources collected from satellites or providing high-frequency information about water use at the farm level. I also discuss the role of trade in the analysis of climate change impacts on agriculture in subsection 3.11.

I conclude section 3 addressing various questions that still seem unsettled and where more research is likely needed (subsection 3.12). For instance, there is insufficient work on the economic of agricultural innovation in the context of a changing climate. For instance, it is unclear whether current levels and the current nature of agricultural R&D is adequate in a rapidly changing climate. In addition, there are many lingering uncertainties regarding the important of changing pest pressure as well as the rise of soil salinity in a warming world. There is also little emphasis on climate justice.

Section 4 provides more practical and hands-on guidance regarding common empirical tasks in this area of research. The chapter is accompanied with reproducible R code that illustrates how to perform many of these tasks in a systematic way. Providing the accompanying code seems important for new researchers entering this field because many of the data management and estimation techniques are yet not standard in agricultural economic curricula. The code provided can be easily adapted to new projects and accelerate the learning curve of new entrants. For instance, the section provides an overview on how to efficiently
aggregate point and gridded weather datasets (subsections 4.1 and 4.2). The techniques that I introduce are based on matrix algebra and sparse matrices to speed up aggregation relative to standard “canned” functions in R packages.

An important empirical consideration in the analysis of the effects of extreme weather and climate change on agriculture is the presence of nonlinearities and thresholds. Climate change will lead to more frequent extreme weather and thus capturing such nonlinearities is critical. Importantly, temporal and spatial averaging of weather conditions can conceal exposure to extreme weather and thus more advanced techniques are required to overcome such obstacles. In subsection 4.3 I describe how to estimate non-linear effects of weather variables semi-parametrically based on bins representing the entire distribution of time exposure to varying environmental conditions (e.g. temperature). I also describe how to construct these datasets. The R code provided illustrates not only how to construct these data but also how to estimate these models. I also clarify certain misconceptions and confusion regarding the estimation of these models. In subsection 4.4 I also present a two-dimensional generalization of the semi-parametric model above that allows simultaneously for non-linear and within-season varying effects. This is particularly valuable when trying to capture varying sensitivities to environmental conditions within the growing season.

A common feature of agricultural and climate data is spatial dependence, which generally translates into spatial dependence in a regression setting. Subsection 4.5 introduces a few approaches to deal with this by either correcting for spatial dependence or by harnessing spatial dependence to obtain a more efficient estimator. Finally, subsection 4.6 discusses common robustness checks in the literature as well as strategies to present these in a concise manner in a “specification chart”. I also provide reproducible code to conduct these sensitivity checks.

I finally conclude in section 5 where I provide some final thoughts about the potential for new collaborations and for enhancing the impact of economic research in this field.

2 Basic concepts and data

Here I discuss basic concepts and terminology regarding climate change and how farmers respond to it. This preliminary step is critical in helping new researchers understand the common language used in this field.
2.1 Weather and climate

Throughout this chapter I refer to “weather” and “climate” which are related but distinct concepts. A useful way to characterize their relationship is to think about weather as a random variable representing the state of the atmosphere. That random variable could represent, say the “average temperature during the month July in Ithaca, NY”. The value taken by this variable on a given year represents weather conditions.

In contrast, “climate” refers to the moments of the probability distribution of that random variable. Thus, quantities such as the “long term average” or the “inter-annual variability” of this random variable relate to climate. It is often the case that climatologists (and economists by extension) refer to “climatology” as the 30-year average of a weather variable, and as “climate variability” as the inter-annual variance of a weather variable. This concept is different from the term “intra-annual weather variability” which refers to the variability of weather conditions between contiguous time periods within a season or the year.

As a result, the term “climate change” refers to the change in the long term distribution of weather conditions at a given location. By definition, it is a long term process because climatologies are defined over several decades. It follows that climate change eventually results in the rising frequency of weather events that were previously considered unusual or extreme. That being said, because of natural variability in the climate system, a sequence of extreme weather events is not evidence of climate change per se. Indeed, assessing changes in climate requires a relatively long time series of weather observations.

In addition, the term “climate change” should also not be conflated with “weather change” which may refer to either inter-annual or intra-annual fluctuations in weather conditions depending on the context. Moreover, recent weather trends should not be conflated with climate change. There are well known cyclical components in the climate system such as El Niño-Southern Oscillation (ENSO) which are linked to cyclical changes in weather patterns in various parts of the world. These multi-year weather patterns do not constitute climate change, though climate change may alter their intensity.

Climate change can have both natural or human causes. An entire field in climate science called “detection and attribution” focuses on determining whether observed historical changes in climate can be attributed to specific causes. The term “anthropogenic climate change” thus refers to changes in climate that have been shown to originate from human activities, including through the emissions of greenhouse gases.

Making the clear distinction between weather and climate is important. Not only does it help avoid ambiguous terminology and helps convey ideas more clearly, but it also has economic implications. The reason is that while economic agents cope directly with weather conditions, they actually form expectations about climate.
2.2 Adaptation

According to the [IPCC (2014)], adaptation to climate change in human systems is “the process of adjustment to actual or expected climate and its effects, in order to moderate harm or exploit beneficial opportunities”. It should be clear why assessing the potential impacts of climate change on agriculture should require considering the degree to which farmers would adapt to a new climate. Not accounting for adaptation would naturally overstate potential damages and underappreciate potential opportunities.

Agricultural economists have mostly focused on adaptation undertaken by farmers. If you consider weather as a stochastic essential input, then the adjustments of traditional inputs under the control of the farmer to maximize profit or utility in response to weather fluctuations are forms of farmer adaptation. Input decisions are typically sequential in nature (Antle, 1983), so certain decisions are committed irreversibly early in the season (e.g. crop and parcel choice, acreage, etc.) before the farmer gets to observe the weather realization. As a result, some inputs remain fixed throughout the growing season, constraining the farmer to a limited range of adaptations. In general, these short-run adaptations to weather fluctuations underestimate the range of adaptations undertaken by farmers when considering long run adjustments in response to a changing climate.

However, certain short run adjustments may not be available to the farmer in the long run. One example may be irrigation. For instance, a farmer with land equipped for irrigation may increase the amount of water used in response to dryer weather conditions. However, if the source of irrigation water is projected to be depleted or water prices are expected to be much higher in the future, then adjustments made in the short run may not be indicative of those available in the long run.

The empirical characterization of future farmer adaptations generally relies on historical behavior. But past behavior relative to a change in a weather shock (or small changes in climate) could mischaracterize the degree to which farmers may adapt in the long run. This is somewhat related to the Lucas critique applied to the climate change context (see Kahn, 2014).

Accounting for adaptation is critical to the estimation of potential future climate change impacts on agriculture. This has been a major emphasis in the literature. Not accounting for adaptation would naturally overstate damages. Thus researchers typically seek to constrain or characterize their findings depending on the degree to which farmers can adapt in their modeling approach.

Capturing or measuring long run adaptations to climate change is challenging. It ultimately requires capturing adjustments to the production process in response to a long term change in the distribution of weather conditions. Ideally, characterizing this process requires
a long time series of weather and production decisions. Long longitudinal datasets with detailed information about production practices are very rare, making detection of adaptation activities elusive.

Explicitly accounting or modeling all possible farmer adaptation to a changing climate is intractable. Farmers have numerous potential adjustments to their production decisions. This could include changes in input use, tilling practices, planting dates or crop mix for crop production, or the change in management, feed, animal breeds, equipment or infrastructure for livestock production. As a result, researchers often rely on indirect evidence to identify or quantify adaptation (or lack of).

The IPCC (2014) also employs the term “maladaptation” which refers to “actions that may lead to increased risk of adverse climate-related outcomes, increased vulnerability to climate change, or diminished welfare, now or in the future”. However, this term is rarely used in mainstream economic academic discussions. In the agricultural context, this would mean that agriculture is growing more vulnerable to climate change, such as becoming increasingly sensitive to higher temperature (e.g. Lobell et al. 2014; Ortiz-Bobea et al. 2018, 2020). However, such changes in sensitivity to extreme temperature may result from an optimal tradeoff so referring to such phenomena as maladaptation which carries a undesirable connotation may be misleading.

Note that the notion of economic efficiency is absent from the IPCC characterization of adaptation. Economists bring a unique perspective to analyze the economic desirability of adaptive investments from a welfare perspective. This is more often than not absent for the analysis and discussions surrounding adaptation.

2.3 Weather data

Weather data is a fundamental component of conducting empirical analysis of climate change impacts and adaptation. Here I highlight some key features of such data without being exhaustive. I encourage readers to consult Auffhammer et al. (2013) for a complete guide on how to use weather data and climate model output in economic analysis.

Basic weather variables like air temperature and precipitation are commonly measured in weather stations. These are commonly (but not always) government-run facilities with the necessary instrumentation to record information about atmospheric conditions. In these facilities, temperature has historically been measured directly via thermometers, whereas precipitation is measured via rain gauges, which measure the amount of precipitation falling within a time interval, typically a day. In certain countries like the US and parts of Western Europe, this instrumental record dates back to the 19th century. Air temperature varies
throughout the day, and it is sometimes possible to obtain hourly data for certain regions in recent years. But data is more commonly available at the daily, monthly or annual scales. In such cases summary statistics are reported including maximum, average and minimum temperature or total precipitation over the given time period. Note that strict rules and protocols govern the recording and reporting of official weather data.

Temperature measurements prior to the use of thermometers are based on proxy variables (e.g. tree rings) and are used to reconstruct past weather conditions in paleoclimatology. Since the late 1970s, researchers can also obtain remotely-sensed temperature from satellites which are derived indirectly from microwave radiation.

Because temperature and precipitation are commonly measured at specific locations (weather stations) throughout the landscape, such type of weather data is referred to as “point data” in Geographical Information Systems (GIS). A point is associated with precise geographical coordinates and is thus said to be geo-referenced.

Figure 1A provides an overview of the spatial distribution of the more than 100,000 weather stations reporting daily information in the Global Historical Climatology Network (GHCN) in 2020. The GHCN is the world’s largest database of climate summaries from land surface stations across the globe and it is managed by the National Oceanic and Atmospheric Administration (NOAA). The distribution of weather stations can be very sparse across the world, even within countries like the US (Fig. 1B). This spatial sparsity raises challenges for obtaining correct weather information in areas located far from weather stations, particularly when the landscape has pronounced orography. In section 4.1 I provide a brief and reproducible introduction on (very) basic weather station data interpolation.

With the goal of providing more complete spatial coverage in a consistent fashion, climatologists have developed “gridded” weather datasets based on various interpolation techniques. These interpolation techniques often rely on elevation and other physical factors that are known to affect both temperature and precipitation. These procedures are considerably more sophisticated than a simple spatial interpolation. These geo-referenced datasets come on a regular grid and are referred to as “raster” data in GIS. They are characterized by a spatial resolution, often measured in degrees or distance. Raster data is fundamentally structured as a matrix, where each entry corresponds to a patch of of the Earth’s surface.

It is important to clarify that some of gridded weather datasets can sometimes incorporate numerical weather models (similar to those used for weather forecasts). In that case these gridded weather data are referred to as “reanalysis”. This is one example of “modeled” data that incorporates both observations (from weather stations) and information from a mechanistic weather simulation model. The advantage of such data is that they can provide a spatially and temporally consistent field of weather information even when there are gaps
Figure 1: Spatial distribution of weather stations in the Global Historical Climatology Network in 2020.
in the underlying weather station data. They can also provide output of variables that are actually not being actually measured in any consistent way (e.g. temperature or wind speed at high altitudes).

So far I have only discussed weather variables and data relating to atmospheric conditions. For certain applications the researcher might be interested in more direct measures of water content or temperature in the soil. Direct measurement of soil water content and temperature are very rare and only available over limited areas and time periods in a handful of nations. Obtaining data on these variables at larger scales generally requires relying on modeled data, although new satellite sensors are increasingly able to indirectly measure some of these soil moisture variables.

The evolution of soil water content and temperature is a complex process that is typically modeled with a Land Surface Model (LSMs). An LSM takes “forcing” or exogenous variables as inputs (e.g. surface temperature, precipitation, wind, air humidity, etc.) to characterize the evolution of soil conditions over time. Some of the key variables of interest include soil water content but also soil temperature. These models provide a modeled snapshot in time of these variables at various depths in the soil, often down to a couple meters. The use of certain highly detailed LSM datasets can be cumbersome as they may require manipulating terabytes of data. For some applications, the use of simpler drought indices, such as the Palmer Drought Severity Index (PDSI) or the Standardized Precipitation Index (SPI), may suffice (see Heim, 2002). These indices seek to approximate water deficit conditions based on water supply (precipitation) and demand (evapotranspiration and runoff) with relatively simple algorithms.

In table 1 I include a list of commonly used gridded weather and land surface datasets with at least a daily temporal resolution. This list is by no means exhaustive but provides the reader with a starting point in their analysis. Monthly datasets are easier to come by and typically offer longer temporal coverage. For instance, the widely used monthly version of Oregon State University’s Parameter-elevation Regressions on Independent Slopes Model

| Name  | Spatial Coverage | Temporal Resolution | Source                  |
|-------|------------------|----------------------|-------------------------|
| PRISM | CONUS            | 4 km                 | 1981 – daily            | Daly et al. (1997)      |
| Daymet| North America    | 1 km                 | 1980 – daily            | Thornton et al. (2014)  |
| NARR  | North America    | 0.3 deg              | 1979 – 3-hourly         | Mesinger et al. (2006)  |
| NLDAS | North America    | 0.125 deg            | 1979 – hourly           | Xia et al. (2012)       |
| GLDAS | Global           | 0.25 deg             | 1948 – 3-hourly         | Rodell et al. (2004)    |
| GMFD  | Global           | 0.25 deg             | 1948 – 2016 daily       | Sheffield et al. (2006) |

Table 1: Commonly used gridded weather datasets.
(PRISM) dataset over the contiguous United States (CONUS) is available since 1896.

An important point regarding empirical work in this literature is the common mismatch in spatial resolution between agricultural and weather data. Agricultural data is often available to researchers after being aggregated to administrative units such as counties, states or even countries. This aggregation is sometimes performed from micro-data from surveys or census to preserve anonymity of individual farmers. Unless a researcher is dealing with field or farm-level data, the spatial resolution of agricultural data is typically coarser than that of gridded weather data. That is, several grid cells fall within the boundaries of the administrative unit. As a result, researchers end up aggregating the gridded weather data to the administrative unit level.

This naturally raises the question of how should gridded weather data be aggregated to administrative levels. Certain administrative units (e.g. US states) can be fairly large and heterogeneous and contain areas with little to no agricultural activity (e.g. like high mountains or deserts). In other words, weather conditions in certain parts of the administrative unit may be irrelevant for agricultural production within that unit. A common practice is to rely on fine scale land cover data (e.g. cropland, pastures, or a combination) to use as an aggregation weight. Land cover data comes in raster format and with spatial resolutions ranging anywhere from 30m to 1km depending on the region of the world.

To illustrate this point, Fig. 2A shows maximum temperature in California on August 16, 2020 when possibly the highest temperature ever recorded on Earth (54.4 °C) was measured in the Death Valley (darkest shade of red). This daily gridded data is from PRISM and shows wildly varying weather conditions across the state on the very same day. However, agriculture is mostly concentrated in the Central Valley region. This can be seen in Fig. 2B showing the share of cropland within each PRISM grid cell. A common practice is to aggregate the weather (panel A) variable within each county (or within the state) based on weights proportional to the cropland cover (panel B). The large climatic variations within California illustrate how critical land cover information can be for representing environmental conditions within administrative units.

Intuitively, spatial weighting procedures should make little difference if we are located in a relative small or homogeneous administrative units. However, potentially substantial differences could arise between different weighting schemes in the presence of climatically diverse units. Some have suggested that the weighting should be performed by value (rather than land cover) although it seems unclear how livestock would be accounted for in such circumstances. One way to think about issues about spatial aggregation is to frame it in terms of measurement error. It turns out that implications of these practices have not been characterized. Researchers often end up showing regression results under alternative
Notes: Panel A shows maximum temperature corresponding to August 16 of 2020 over California. This is gridded daily data from PRISM. Panel B shows the share of cropland contained in each of the PRISM grid cells. The grid cell share was derived from finer scale 30m land cover data for 2016 from the National Land Cover Database (NLCD).

Figure 2: Gridded data and cropland land cover in California.
weighting schemes to assuage concerns during the peer review process. This practice seems
suboptimal and more systematic analysis of the consequences of various strategies of spatial
data aggregation are needed.

There are also issues regarding temporal aggregation in weather data. Aggregating
weather data over time can also result in measurement error if the weather conditions are
non-additive and if non-linearities in exposure to various levels of weather conditions are
important, which they likely are.

2.4 Climate models

Climate scientists have developed Global Circulation Models (GCMs) to simulate the evolu-
tion of the climate system. These models are fundamentally similarly to numerical weather
models used in weather forecasting, but incorporate a more complete representation of en-
ergy exchanges between land, oceans, sea ice and the many layers of the atmosphere. Central
to these models are the Navier-Stokes equations, partial differential equations that describe
the movement of viscous fluids. Solving these equations to describe moving air masses in
three dimensions requires considerable computational power, which is why running these
models requires super computers. Major countries have research groups and labs with their
own version of these models.

In order to learn more about factors affecting our climate system, modeling groups have
joined a global inter-comparison project called the Coupled Model Inter-comparison Project
(CMIP). Four of such inter-comparisons have been completed (CMIP Phases 1, 2, 3 and 5)
and there is one under way (CMIP Phase 6 or CMIP6). The key feature of CMIP is the
parallel implementation of identical climate experiments across a wide range of GCMs. Some
of these experiments are designed to learn about specific aspects of these models, so that
GCMs can be improved. However, some of these climate experiments are much more policy
relevant and seek to understand how the global climate system is influenced by anthropogenic
influences.

Various experiments seem particularly policy relevant and are commonly used by economists.
Using CMIP6 terminology, these include the Shared Socioeconomic Pathways (SSPs, see Ri-
ahi et al. 2017), including SSP1-2.6, SSP2-2.5, SSP3-7.0 and SSP5-8.5. The SSPs correspond
to different scenarios about the nature economic development and the pathway of climate
forcing (e.g. emissions) throughout the century. The appended numbers to these scenarios
(i.e. 2.6, 4.5, 7.0 and 8.5) represent the additional radiative forcing on our climate system
in Watts/m² in the year 2100. The higher the number, the higher the additional radiative
forcing, and the higher global temperatures are projected to rise. These scenarios are anal-
ogous to the Representative Concentration Pathways (RCPs) scenarios used in CMIP5, and the Special Report on Emissions Scenarios (SRES) used in CMIP3. Researchers can relate these projected future states of the atmosphere under various GCMs and SSPs with the “historical” experiment that seeks to replicate the conditions of our historical climate system from the nineteen century through 2015 in the case of CMIP6. The “historical” experiment considers both historical levels of both natural (e.g. volcanic eruptions from el El Chichón in 1982 and Pinatubo in 1991) and anthropogenic forcing (e.g. greenhouse gas emissions since the industrial revolution).

Other relevant climate experiments that are relatively underused by economists are the “historicalNat” in CMIP5 and “hist-nat” in CMIP6. These experiments run a historical simulation but only with natural forcing. That is, the output of these experiments provide a counterfactual sequence of modeled weather trajectories that exclude human influence from the climate system. In climate science, the comparison of these experiments and the “historical” experiment is a foundation of attribution studies that seek to establish to what extent extreme weather events (e.g. heat waves) are likely to arise because of human influences, and not because of natural variability. Some studies have used this approach to analyze the historical impact of anthropogenic climate change on agriculture (See section 3.7).

It should be noted that output from climate models is gridded in nature (raster format) and can be manipulated in the same way than gridded weather datasets previously discussed.

Finally, it is worth noting that the CMIPs serve as the basis of the Assessment Reports (AR) for the first working group (WGI) of the Intergovernmental Panel of Climate Change (IPCC) charged with describing the physical basis of the factors affecting our climate system. In fact, the name of the CMIP and the AR are in phase, so that the lessons from CMIP6 feed into the the Sixth Assessment Report of AR6. The ARs serve as an input for international negotiations regarding adaptation and mitigation of anthropogenic climate change within the United Nations Framework Convention on Climate Change (UNFCCC).

### 2.5 Degree-days and agriculture

A growing number of studies rely on variables representing “degree days”, “growing degree days” (GDD), “damaging degree days” (DDD), “extreme degree days” (EDD) or “killing degree days (KDD) for analyzing the effect of cumulative temperature exposure on agricultural production. Although the growing popularity of degree-day measures seems relatively recent in agricultural economic research, the concept has roots that are centuries-old (Réaumur, 1735). Here I provide a brief background on the concept and how to compute these variables.

A degree-day is one of the many units of measurement of thermal time. Thermal time is
a physical quantity measured in units of temperature × time. This concept is very familiar to scientists studying phenology, which is the study of how the periodicity of biological cycles are influenced by their environment. The concept emerged as an heuristic tool to predict the length of the different phases of plant life cycles (Réaumur, 1735). Some measures of thermal time are highly correlated with the timing of numerous phenological events, or cyclical natural phenomena, such as insect or plant development. In plants, such development phases are typically signaled by the appearance of new and differentiated organs such as the emergence of subsequent leaves and flowers or the formation of fruit. French scientist René-Antoine Ferchault de Réaumur laid the foundations of thermal time in the eighteenth century as recalled by Wang (1960): “He summed up the mean daily air temperatures for 91 days during the months of April, May and June in his locality and found the sum to be a nearly constant value for the development of any plant from year to year.” Thermal time subsequently became a pivotal concept in phenology (Hudson and Keatley, 2009, ch. 1).

Indeed, the timing of many biological cycles, particularly in plants and insects, is closely correlated with thermal time accumulation. For this reason, biologists coined a term that measures thermal time accumulation, Growing Degree-Days (GDD). This biological thermal time corresponds to cumulative temperature during a period of time. Intuitively, it is an amount of accumulated exposure to heat. This quantity is often defined mathematically. As shown in equation 1, thermal time \( T \) is typically expressed as a function of two temperature thresholds, \( h \) and \( \bar{h} \) and two points in time, \( t_0 \) and \( t_1 \).

\[
T(\bar{h}, h, t_0, t_1) = \int_{t_0}^{t_1} H(t)\,dt \quad \text{where} \quad H(t) = \begin{cases} \bar{h} - h & \text{if } h(t) > \bar{h} \\ h(t) - h & \text{if } h(t) \in [h; \bar{h}] \\ 0 & \text{if } h(t) \leq h \end{cases}
\] (1)

This definition implies that any measurement of thermal time is a function of the two temperature thresholds and a duration. In fact, the two temperature thresholds, \( h \) and \( \bar{h} \), are experimentally determined to yield a nearly linear relationship between thermal time accumulation and biological development.

The link between temperature and the timing of biological cycles can be explained at
the molecular level within cells. Air temperature, at the most basic level, affects cellular function, and animals and plants have developed strategies to take advantage of climatic conditions conducive to their growth and largely avoid conditions that are harmful. In the case of crops, when air temperature is below the lower threshold, \( h \), also referred to as the crop-specific “base temperature,” or above the higher threshold, \( h \), crop development essentially stops (Ritchie et al., 1991; McMaster and Wilhelm, 1997). Enzymes, which are proteins that accelerate biochemical reactions within cells, become too rigid at low temperatures and coagulate at very high temperatures, leading to slow or entirely inhibited crop growth (Bonhomme, 2000). In other words, because plants cannot regulate much their own temperature, their metabolism is subject to outside temperature, which affects the speed of biochemical reactions.

This relationship is not perfectly linear because the timing of these development stages are also dependent on adequate light, water, and nutrients in addition to appropriate temperature. However, temperature remains the major factor explaining the timing of development stages. This explains why agronomists and farmers use GDDs to estimate stages of crop development and weed and pest life cycles.

Note that variables that measure the amount of time exposed to certain temperature levels are closely related to the concept of degree days. Degree day are measures of cumulative temperature exposure between two temperature thresholds. The concept is very general and is used outside of agronomic sciences. For instance, engineers and energy analysts rely on Cooling Degree Days (CDD) and Heating Degree Days (HDD) to predict energy consumption for cooling in the summer, and for heating in the winter, respectively.

Possibly the oldest use of degree days was to predict phenology, the timing of life stages in plants and certain animals (Réaumur, 1735). The modern incarnation of this concept applied to plants is reflected in the modern use of Growing Degree-Days (GDD) which are precisely reserved to predict crop stages (Bonhomme, 2000). Field crops are characterized by their crop maturity rating which indicates the amount of “cumulative temperature” measured in GDD to reach maturity. Short-season cultivars require less heat of the growing season to reach maturity. For this reason such cultivars are used in colder climate in temperature countries like the US, where the non-freezing period that is fatal to most crops is relatively short. Thus, farmers choose a crop maturity rating based on their local climate.

The implication is that once farmers plant a given cultivar, unexpectedly warm or cold conditions can accelerate or delay the timing to reach crop maturity and harvest. As a result, changes in GDD can affect yield, because shortening the time the crop spends on

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3Organisms unable to actively regulate inner temperature to favorable levels are coined “ectotherms”. This is not only the case of plants, but also of “cold blooded” animals such as insects, reptiles, etc.
the field shortens the time the crop has to accumulate biomass. Similarly, lengthening the timing the crop spends on the field can expose the crop to perilous conditions at the end of the season (e.g. damaging Fall frost). However, the concept of GDD is not intended to predict yield, but to predict phenology. Many economic studies rely on “GDD” measures to predict yield. This is incorrect. A more rigorous use of the term that does not introduce confusion with its agronomic use is to simply describe degree day variables in terms of the range of temperature used to defined them, like “degree days 8-30°C”. Note that degree days capturing exposure to relatively high thresholds, say 30°C, are commonly referred to as Extreme Degree Days (EDD), Killing Degree Days (KDD) or Damaging Degrees Days (DDD). Similarly, describing degree days by their threshold, such as “degree days over 30°C” seems generally more appropriate.

3 Climate change impacts and adaptation

This section provides an overview of the main research questions and the methods used to evaluate climate change impacts and adaptation in the agricultural sector. While the discussion will cover developments over the past 2 decades, I put some emphasis on the evolution of the literature as well as recent contributions. I also spend some time discussing unresolved or relatively unexplored research questions. I also invite the reader to consult several overview articles on methods of assessing climate change impacts on agriculture and other sectors, including Blanc and Schlenker (2017), Carter et al. (2018) and Kolstad and Moore (2020), to name just a few.

3.1 Biophysical approaches

Most of the early work assessing climate change impacts on agriculture is fundamentally based on biophysical models (e.g. Adams 1989; Adams et al. 1990; Rosenzweig and Parry 1994). These plant science models mechanistically characterize the effect of environmental conditions (e.g. sunlight, water availability, air and soil temperature, carbon dioxide concentrations, air humidity, etc.) on the physiological processes that underly crop yield formation. This type of approach typically assume farmers adopt a series of more or less sophisticated management practices including choice of cultivar, fertilization decisions, planting time, etc. These models are subsequently coupled with climate models and supply-demand economic models to simulate the effect of climate change on agricultural production and welfare. I revisit the integration with economic models in subsection 3.11 on market equilibrium and trade.
One of the main advantages of biophysical approaches is that they can provide a transparent understanding of the exact channels through which climate change impacts occur. For instance, these approaches allow unpacking the role of CO\(_2\) fertilization as well as which crops and regions of the world would be more affected. Relying on a supply and demand model also allows to compute welfare effects of climate change and how they are distributed among consumers and producers in various regions of the world.

However, these approaches present various limitations. Because these models are not directly rooted on observational data, it is unclear whether the assumptions about farmer behavior may be realistic in real-world settings. These approaches are also deterministic, so they don’t directly provide a measure of uncertainty regarding the relationship between changes in the distribution of weather conditions and agricultural outcomes. In general, these model need to be extensively and carefully calibrated to perform well within the sample and tend to perform poorly when used out of sample. In fact, a key criticism of this approach is that results tend to be highly dependent on the crop model used, which has led some call for an overhaul of modeling approaches that favor multi-model ensembles (Rötter et al., 2011).

An important development in this literature the Agricultural Model Intercomparison and Improvement Project (AgMIP, \url{https://agmip.org}), which aims to improve biophysical crop modeling (Rosenzweig et al., 2014). Similarly to CMIP models, intercomparison projects allow modelers to compare model outputs based on identical scenarios and to learn about the sources of discrepancies across individual models. The consensus seems to be that the future of biophysical crop modeling resides with multi-model ensembles.

Moving to multi-model approaches not only facilitates model improvements, but also allows researchers to sample from a wider range of crop models when conducting climate change impact analyses. This helps better characterize model-driven uncertainty of climate change impact projections.

Although the development to multi-model ensembles seems welcome, it also means that research projects in this area involves relatively large pre-established teams which can present a barrier to entry for individual researchers, especially students. However, there seems to be an important role for economists to play in the coupling of these multi-model ensembles with supply-demand and trade models.

Finally, a present limitation of biophysical approaches is the major emphasis on the major staple field crops such as wheat, corn and rice. Cereal crops represent about a fifth of the total agricultural value produced so these approaches have so far overlooked the effects on many other parts of the global agricultural sector. There is a limited number of models focused on specialty crops or livestock production, which seem like important directions of research. But then again, models are likely to do well within the region of calibration and
pose limitations when trying to apply these models to other regional contexts. See Antle and Stöckle (2017) for a review of the use of process-based models along with economic models.

3.2 The Ricardian approach

The introduction of the Ricardian approach in Mendelsohn et al. (1994) was a reaction to earlier studies based on biophysical approaches that allowed for relatively little farmer adaptation to climate change (e.g. Adams, 1989; Adams et al., 1990; Easterling et al., 1992; Kaiser et al., 1993; Adams et al., 1995). In retrospect, these studies unsurprisingly tended to point to relatively large damages primarily driven by losses in crop yields.

The idea behind the Ricardian approach is that one can assess future climate change impacts capturing the full range of farmer adaptations without having to model these adaptive choices explicitly. The key conceptual assumption is that farmers are already adapted to their local climate. That is, they would have adopted production practices and choices that are the most beneficial given the local climate, prices and technology. Because land is a fixed factor of production, the demand for land generates economic rents. The discounted stream of these rents are capitalized in the value of land. So if these rents originate from more beneficial climatic conditions, then climate would be capitalized in the value of land.

Empirically, the Ricardian approach attempts to recover the marginal value of climate by exploiting the cross-sectional spatial variation in farmland values and climate across a large region. This constitutes a hedonic analysis of the characteristics of land (Rosen, 1974; Palmquist, 1989). The regression can be expressed as:

\[ y_{it} = \bar{Z}_{it}\beta + X_{it}\gamma + \alpha_t + \epsilon_{it} \] (2)

where \( y_{it} \) is farmland value per acre in location \( i \) (e.g. county or district) and year \( t \), \( \bar{Z}_{it} \) is a vector of climate variables defined over the previous 30 years (\( \bar{Z}_{it} = \sum_{s=t-30}^{t-1} Z_{is}/30 \)), \( X_{it} \) is a vector of control variables, \( \alpha_t \) is a year fixed effect and \( \epsilon_{it} \) is an error term. The hope in this analysis is that the inclusion of control variables will reduce concerns regarding omitted variable bias and lead to unbiased estimates of \( \beta \).

The researcher can then couple these hedonic estimates of the marginal value of climate on farmland values \( \hat{\beta} \) with climate change projections \( \Delta \bar{Z}_i \) to derive climate change impacts \( \Delta \hat{y}_i = \Delta \bar{Z}_i \hat{\beta} \). In principle, these impacts account for the full range of farmer adaptations.

The first implementation of the approach (i.e. Mendelsohn et al., 1994) was in the context of US agriculture and relied on county-level farmland values from the 1978 and 1982 Census of Agriculture. The main specification estimated these 2 cross-sections separately.
and regressed farmland value per acre on linear and quadratic terms of seasonal (January, April, July, October) temperature and precipitation along with a series of physical (e.g. average soil characteristics) and economic controls (e.g. population density and income per capita).

The most striking finding at the time was that applying a uniform warming of 5°F warming and a 8% increase in precipitation, an approximation of early IPCC projections, suggested slightly beneficial impacts for US agriculture. However, the results were substantially different depending on the regression weights used in the analysis. As indicated by Solon et al. (2015), when regression coefficients differ dramatically with different regression weights, it may be a sign of misspecification or un-modeled heterogeneity. The results were nonetheless in stark contrast to previous work.

The approach and the implementation in Mendelsohn et al. (1994) generated considerable criticism (see Cline 1996; Kaufmann 1998; Darwin 1999; Quiggin and Horowitz 1999). As summarized in Schlenker et al. (2005), the main criticisms included (1) that the Ricardian approach does not account for adjustments costs, (2) that the regression results were not stable across regression weighting schemes, and (3) the inappropriate treatment of irrigation. This last point probably gained the most traction. Farmers in certain regions can rely on a water supply for irrigation instead of directly from precipitation. As a result, the shadow value of climate should in principle differ across irrigated and non-irrigated regions. Econometrically, that means that the researcher should estimate separate coefficients for irrigated and non-irrigated areas. A simple dummy for irrigation would not suffice as that simply alters the intercept.

This precise idea was proposed in Schlenker et al. (2005) which showed that when the MNS model is restricted to the mostly non-irrigated Eastern half of the US, the Ricardian model points to large negative damages, rather than benefits. Results also become stable across regression weights. In a related study, Schlenker et al. (2006) proposed a new set of climate variables including degree days variables commonly used for predicting crop phenology and plant biomass growth. The main results mirrored the findings of Schlenker et al. (2005). Interestingly, the results in Schlenker et al. (2006) were robust to the inclusion of state fixed effects. This is striking because it means that warmer areas within states, tend to exhibit lower farmland values even after controlling for land quality characteristics and other economic controls such as population density and income per capita.

Various improvements to the Ricardian approach have been introduced over time. Timmins (2005) notes that Ricardian estimates may be biased when land is heterogeneous within locations (e.g. counties) and land owners allocate land use optimally. This problem arises due to spatial or administrative aggregation of data of parcels under different land use and
with differing shadow values of climate. Fezzi and Bateman (2015) also point out issues related to the common issue of spatial aggregation in Ricardian models. Using a detailed database of land values for Great Britain, they find that aggregation conceal important interactions between temperature and precipitation. This results in substantial biases in projection of climate change impacts. This is particularly problematic for this literature given that farmland value data is often only available at aggregate scales for privacy reasons.

Farmland values reflect expectations about future land rents. Severen et al. (2018) point out that if land market players expect climate change to affect future rents, then those expectations should be capitalized as well, biasing Ricardian estimates. They test whether climate change projections (based on two GCMs) appear to be already capitalized in US farmland markets using a cross-sectional approach. The paper subsequently proposes a corrected “forward-looking” Ricardian approach that addresses this potential bias. One potential shortfall of this implementation is that the test is based on cross-sectional evidence, so it is unclear if climate change projections are correlated with unobservable determinants of land values. An alternative approach would be to track changes in farmland values over time as more information about climate projections is made public. Another challenge here is that the US public views regarding the existence and origin of recent climate change are highly polarized between urban and rural areas across the US (Leiserowitz et al., 2013). Thus the regional divided in these views could be correlated with the extent of non-farm pressures on farmland markets.

More recently, Ortiz-Bobea (2019) revisited the Ricardian analysis of US farmland values and found that large damages found in previous studies (e.g. Schlenker et al., 2005, 2006) appear to be driven by factors outside the agricultural sector. Essentially, large climate change damage estimates in recent farmland values cross-section appear driven by non-farm omitted variables. Using a century of farmland value data, the study finds that climate change impact estimates are statistically insignificant when relying on older farmland value cross-sections. The study finds that this result stems from major changes in the farmland value cross-section over time. A convergence of evidence suggest such changes in the cross-section are linked to the rise of non-farm pressures which are correlated with climate within states (e.g. rise in recreational demand for land in cooler areas of certain states). These changes in farmland values appear unrelated to technological change or other forces within the agricultural sector. To circumvent biases from the capitalization of non-farm pressures, the study proposes a Ricardian model based on farmland rental prices, rather than farmland asset values. This approach was employed in Hendricks (2018) that conducts a Ricardian analysis of cropland rental prices in the central US to assess the potential gains from innovations that reduce heat and water stress.
The Ricardian approach continues to be used across many contexts. Perhaps its most attractive features are its simplicity and the conceptual elegance of how it resolved previous thorny debates about capturing adaptation. The approach has important drawbacks that seem difficult to overcome. Despite efforts to make the approach more “structural” (Seo and Mendelsohn 2008), it still remains a bit of a “black box” regarding underlying mechanisms that are important for policy or developing priorities for adaptation.

Perhaps more importantly, empirical economics is well engaged in a “credibility revolution” (Angrist and Pischke 2010) where much attention is given to the quality and credibility of research designs. The Ricardian approach is based on an empirical strategy that is fundamentally vulnerable to omitted variables. The identifying variation in the approach comes from the spatial variation in land values and climate. If unobserved drivers of land values, of which there are many, are omitted and happen to be correlated with climate, which is plausible, then estimates are biased. Previously proposed fixes, like the inclusion of state fixed effects do not fundamentally address this issue as shown in Ortiz-Bobea (2019). The inclusion of state dummies that makes the estimation be based on the within-state variation in prices and climate, could actually amplify omitted-variable bias if those operate more strongly within states than across states. Current research standards clearly favor research designs based on longitudinal data in which researchers can convincingly control for time invariant confounders.

Still, a few attempts have been made to control for unknown omitted variables in a cross-sectional setting. That includes the introduction of the Spatial Durbin Error Model (LeSage and Pace 2009; Elhorst, 2010) in Ortiz-Bobea (2016) or that of a “Spatial First Differences” estimator in Druckenmiller and Hsiang (2018). The underlying idea of these approaches is that unobservables may be spatially dependent in a way that slightly differs from that of climate. These approach harness this information to control for or subtract out the influence of these confounders.

3.3 Panel profit and productivity approaches

The use of longitudinal data to analyze the effect of weather conditions on agricultural outcomes has a very long tradition in agricultural economics (Hodges 1931; Schickele 1949; Stallings 1960; Morgan 1961; Stallings 1961; Shaw 1964; Oury 1965; Black and Thompson 1978). This early literature was not initially concerned with climate change, but with forecasting crop production to anticipate price swings, and understanding the nature of agricultural production risk. It was only until the late 1980s (e.g. Adams 1989) that articles exploring empirically the implications of climate change on agriculture started to appear in
leading agricultural economics journals like the *American Journal of Agricultural Economics* (AJAE). However, these initial studies were fundamentally based on biophysical crop models.

The surge in interest in econometric panel approaches to analyze potential climate change impacts on the agricultural sector can probably be traced back to Deschênes and Greenstone (2007), which offered a counter narrative to the negative findings in Schlenker et al. (2005) based on the Ricardian approach. See Blanc and Schlenker (2017) for a review on the use of panel models in assessing climate change impacts on agriculture.

The approach in Deschênes and Greenstone (2007) was to rely on presumably random year-to-year fluctuations in weather conditions to explain variations in profits within US counties. This approach allows controlling for time-invariant omitted variables that may be correlated with climate and may plague the Ricardian approach. Their model can be expressed as:

\[
y_{it} = Z_{it}\beta + X_{it}\gamma + \alpha_i + \alpha_{st} + \epsilon_{it}
\]  

where \(y_{it}\) is net revenue or “profit” per acre in county \(i\) and year \(t\), \(Z_{it}\) is a vector of weather variables (e.g. precipitation and temperature), \(X_{it}\) is a vector of time-varying control variables, \(\alpha_i\) is a county fixed effect, \(\alpha_{st}\) is a state-by-year fixed effect and \(\epsilon_{it}\) is an error term.

Conceptually, the model estimates a short-run effect of climate change on profits. The idea is that farmers cannot adjust many input decisions to unanticipated changes in weather. As a result the effect of weather on profits would be appear more detrimental than it would be if the farmer were able to fully adjust inputs in the long run. Because the study found very small effects of climate change on profits in their implementation, their interpretation is that climate change would have beneficial effects on US agriculture with the current technology.

As pointed out in Fisher et al. (2012), the implementation in Deschênes and Greenstone (2007) suffered from a series of shortcomings. Among the main issues were problems related to weather data quality which tend to attenuate the magnitude of the \(\beta\) coefficients. Another concern is the inclusion of state-by-year fixed effects \(\alpha_{st}\) which arguably “wipe out” a lot of the weather variation used to identify effects on profits. The main issue is that with so little variation within state-year, estimates might be imprecise and potentially more vulnerable to biases associated with measurement error (see Griliches and Hausman, 1986).

A conceptual limitation of the Deschênes and Greenstone (2007) implementation is the nature of the outcome variable. The study constructs a “profit” variable from the US Census of Agriculture by subtracting total county expenses from total sales divided by the acres of land in farms. Technically this is a net revenue variable that can be problematic in the analysis. The potential issue relates to the role of inventories, which farmers use in a countercyclical manner to smooth the effect of unusual economic and weather conditions.
That is, on a bad year, a farmer may sell more than they produced, whereas she might sell less than what is produced on a good year. Similarly, farmers may avoid large purchases (e.g., tractor) in bad years whereas they might go forward with them in good years. This behavior will tend to bias contemporaneous weather effects toward zero. One potential fix to this issue is to estimate a distributed lag model to account for weather shocks in previous years (see Deschênes and Greenstone 2012).

When some of the concerns above are addressed (see Fisher et al. 2012 and Deschênes and Greenstone 2012), the projected impacts of climate change on profits are negative. It would seem as if the degree to which these effects are large or small lies on the eye of the beholder, particularly on how these short-run effects translate to long-run effects. Indeed, this panel approach only accounts for farmer adjustments that could happen within the year (or a couple of years with a distributed lag model).

More recently, a few studies have relied on measures of Total Factor Productivity (TFP) rather than on net revenue variables. A key advantage is that TFP data, when well-constructed, accounts for changes in inventory. For instance, the Economic Research Service (ERS) within the US Department of Agriculture (USDA) develops a high quality US state-level TFP panel dataset that can be harnessed for climate-related research. While the spatial resolution is coarser than US Census data (state versus county), the greater temporal resolution (annual) is particularly useful given that identification is based on the within-location variation in weather. Examples of such studies include Liang et al. (2017), Ortiz-Bobea et al. (2018) and Ortiz-Bobea et al. (2021).

Following the framework proposed in Ortiz-Bobea et al. (2021), consider an aggregate production function of the form $Y_{it} = e^{f(Z_{it})}A_{it}X_{it}U_{it}$ where $Y_{it}$ is aggregate agricultural output in state $i$ and year $t$, $e^{f(Z_{it})}$ is the effect of weather, $A_{it}$ is a neutral productivity factor, $X_{it}$ is a measured aggregate input and $U_{it}$ is an unmeasured aggregate input. Taking logs, first differences and rearranging yields the following expression that approximate the growth rate of TFP:

$$\Delta \ln TFP_{it} \equiv \Delta \ln Y_{it} - \Delta \ln X_{it} = \Delta \ln A_{it} + \Delta f(Z_{it})\beta + \Delta \ln U_{it}$$

where $\Delta$ denotes change. By definition, TFP growth is the growth in aggregate output that cannot be explained by growth in measured input. In the proposed model, that TFP growth is the sum of three factors, a technological improvement reflected in $\Delta \ln A_{it}$, a weather effect embedded in $\Delta f(Z_{it})$ and changes in unobserved inputs $\Delta \ln U_{it}$. The key point is that one can harness fluctuations in TFP to capture and characterize the effect of weather fluctuations on agricultural production, net of input responses.

Using this approach, Ortiz-Bobea et al. (2018) analyzes the effect of weather conditions
on US agricultural TFP. The analysis is conducted separately by Climate Hub regions which are agro-climatically coherent regions proposed by USDA for adaptation planning. The key finding in the study is that Midwest agriculture is growing increasingly sensitive to higher temperatures. This is found by conducting a Wald test of stability of regression coefficients between the two halves of the sample. The study also provides some ideas of the drivers. The trend appears related to two compounding factors, the growing sensitivity of the crop output to higher temperatures, and the increasing specialization in crop production in Midwest.

The rising sensitivity to high temperature in Midwest agriculture could appear as a form of “maladaptation” but it remains unclear whether this rising sensitivity results from a desirable tradeoff with higher productivity. More research is needed to better understand these trends, especially regarding the timing of these vulnerability changes over time.

3.4 Statistical crop yield models

A statistical crop yield model typically regresses a panel of crop yields on various weather variables. These models had traditionally been the focus of agricultural meteorologists. See Decker (1994) for a history of that field. However, these models have grown increasingly popular among agricultural economists interested in exploring a specific sub-channel through which climate could affect agricultural production (e.g. Tack et al., 2015; Ortiz-Bobea and Tack, 2018; Shew et al., 2020).

The key strength of these models relative to biophysical approaches is that they are grounded on observational data. This has several advantages. First, these models account for actual farmer management decisions when the data is based on crop yields collected from farmers. Because farmers can sometimes respond to weather fluctuations within the growing season, results can be interpreted as reflecting short run adaptation to weather fluctuations. This interpretation is not really correct when crop yield data are based on field trials in which generally management decision are pre-determined by a researcher.

Statistical crop yield models have also been used to indirectly detect whether farmer adaptation to climate change has already occurred. Two approaches have been proposed. The first is to test whether crop yields are growing less sensitive to extreme weather that are becoming more common under climate change (e.g. high temperatures). This is typically achieved by testing for stability of regression coefficients over time, which naturally requires relatively long panels. But it remains ultimately unclear whether changing coefficients over time result from changes in crop cultivars, changing inputs or management techniques, which constitute some form of adaptation, or from a statistical artifact such as changing weather data quality over time. More emphasis should be given to teasing out the sources of these
changes, ideally by coupling statistical models with other production information (e.g. crop cultivars, data on management, etc.).

The second approach of indirectly detecting farmer adaptation is to test for regional heterogeneity of weather coefficients. For instance, one should expect that farmers in region with greater exposure to high temperature to adapt to such environmental conditions over time. Econometrically, this means that the effect of high temperature should appear to be less detrimental in warmer places than in cooler places. So this check consists on testing for an interaction between a weather variable and its climatology. This is the approach adopted by Butler and Huybers (2013) to analyze adaptation to high temperature in US corn yields. However, this climate is likely correlated with other factors that may affect crop yield sensitivity (e.g. soil quality) so this approach remains vulnerable to time-invariant omitted variables that interact with weather fluctuations.

One important shortcoming of many studies in this area is that they do not inform us about the types of adaptations or inputs adjustments farmers may be engaging. Importantly, the fact that inputs are typically unobserved makes the interpretation of short run effects more difficult. For instance, when a farmer increases irrigation intensity in response to higher temperatures or lack of precipitation means that the effect of these undesirable weather conditions will appear attenuated. In the other hand, if inputs are complementary to weather conditions, farmers may cut labor and fertilization in response to undesirable environmental conditions, which would further reduce crop yields. Thus, depending on the nature of the input response, the estimate yield effect may appear either exacerbated or attenuated. It is critical that researchers acknowledge that farmer input decision are often times correlated with weather fluctuations, and that results should be interpreted accordingly.

Another important area of debate in this literature is the nature of the weather variables and how they are modeled. A fundamental challenge here is the mixed frequency of the data with high-frequency daily weather predictors throughout the growing season affecting the ultimate crop yield at harvest (Ghanem and Smith, 2020). Unlike for the biophysical models, statistical models cannot directly incorporate daily weather conditions. This would represent too many regressors which happen to be highly correlated between neighboring days. As a result, researchers undertake a variable selection more or less based on first principles (e.g. what conditions are known to be important for crop yield determination) and data-driven criteria (e.g. in-sample or out-of-sample measures of model fit or other criteria).

Precipitation and temperature are naturally considered two fundamental climatic variables affecting crop production. Crops need water to grow so precipitation is critical in rain-fed systems. Too little or too much precipitation is presumably detrimental to crop yields, suggesting there is an optimal level of precipitation. Similarly, very cold condition
are detrimental to crop growth and very hot conditions accelerate evapotranspiration and can cause heat stress, so extreme temperature are presumed to be detrimental. This also suggest the existence of an optimal temperature range. As a result, perhaps the most basic crop yield statistical model takes the following form:

\[ y_{it} = \beta_1 T_{it} + \beta_2 T_{it}^2 + \beta_3 P_{it} + \beta_4 P_{it}^2 + \phi_s(t) + \alpha_i + \epsilon_{it} \]

where \( y_{it} \) is crop yield (or its logarithm) in location \( i \) and year \( t \), \( T_{it} \) stands for growing-season average temperature, \( P_{it} \) represents growing-season precipitation, \( \phi_s(t) \) represents a regional time trend (typically a year variable interacted with a regional dummy), \( \alpha_i \) is a location fixed effect, and \( \epsilon_{it} \) is an error term. The introduction of the quadratic terms seek to the existence of optimal levels for temperature and precipitation. However, this imposes symmetry to the response function.

Note how this model reduces dramatically the dimensionality of the problem by averaging and aggregating temperature and precipitation over the growing season. This model boils down the entire growing season to just four variables in an attempt to make the model tractable.

One drawback of averaging temperature over the growing season, is that it conceals the distribution of temperature within the growing season. This was a key contribution in Schlenker and Roberts (2009a), an influential study in this literature. The study estimated the potential impacts of climate change on US crop yields later this century by coupling crop yield models for corn, soybeans and cotton with GCM projections. Its key contribution is the estimation of non-linear effects using a generalization of the concept of degree-days that harnesses the intra-daily distribution of temperature over the growing season. Specifically, the study shows that exposure to temperature above around 30°C are particularly detrimental for these crops. Because anthropogenic climate change is projected to increase the frequency of high temperature, then yields were projected to decline if growing regions and the crop yield response function remain stable. Analogous studies have found large damages from higher temperatures in other regions of the world (Hsiang et al., 2013; Gammans et al., 2017).

Note that the temporal aggregation of temperature conceals its underlying high-frequency distribution. For instance, two days with the same average temperature can exhibit different extrema, so averaging conceals the amount of time exposed to very high or low temperatures. The approach proposed in Schlenker and Roberts (2009a) is to rely on temperature variables that capture the amount of time spent at each temperature interval. I cover in greater detail the technical aspects of how to construct exposure variables as well how to estimate these models in subsection 4.3.
Perhaps one of the most striking findings in this literature is the dominating role that temperature plays in explaining historical variations and future projections of crop yields relative to precipitation. Changes in temperature typically explain about 80 to 90% of the projected climate change impacts. Given the fundamental role that water availability plays in the functioning of plants, this is particularly surprising. To explore this puzzle [Lobell et al. 2013] combines biophysical models to replicate the results obtained using statistical approaches. The study finds exposure to high temperature, as measured by degree days above 30°C, are associated higher Vapor Pressure Deficit (VPD) which contributes to water stress, which negatively affects yield. In essence, the story is that high temperature affects water availability. As result, other studies have relied on VPD as a predictor in statistical crop yields models (e.g. Roberts et al., 2012; Lobell et al., 2014).

The interpretation that high temperature affects water availability raises the question about the appropriateness of precipitation as a measure of water supply. Indeed, season-long precipitation variables are very crude measures of how much water is effectively available to crops. In the same way that temporal aggregation in temperature was potentially problematic, a similar shortcoming affects precipitation. More concretely, it’s not only the amount of precipitation that matters, but also its timing throughout the growing season. When precipitation is highly concentrated over short periods of time, a lot of that water is lost via deep percolation or as runoff. Thus, two growing seasons can have the exact same total precipitation, but one may be considerably dryer than the other.

What this highlights is that precipitation, as a measure of water flow, is not ideal for capturing the yield effect of water availability. In fact, what matters to crops is how much water is effectively available throughout the growing season. Water availability is thus a stock rather than a flow. Unfortunately, there are no widespread network of stations measuring soil water content, even in countries like the US. However, there are model-generated raster datasets of soil water availability obtained from Land Surface Models (LSM). These LSM aim to describe the evolution of soil water content and other factors given a set of exogenous drivers such as soil characteristics, land cover, and fine scale atmospheric conditions (e.g. hourly or sub-daily precipitation, temperature, solar radiation, etc).

To address this concern [Ortiz-Bobea et al. 2019] rely on model-generated measures of soil moisture to unpack the climatic drivers of crop yields for six major US field crops. The study pointed to three main findings. First, the adoption of soil moisture variables substantially improves model fit relative to standard models. Second, climate change impact projections from models based on soil moisture variables remain similar to those from traditional models based on precipitation. Finally, the study finds that accounting for soil moisture reduces the relative role of temperature variables in climate change impact projections. This means, as
hypothesized by previous studies, that temperature effects were partly reflecting the effects of dry conditions in previous models. Note that the relationship between high temperature and drought is not unidirectional. While higher temperature do increase evapotranspiration and reduce soil water content, droughts can also cause temperatures to rise (Seneviratne et al., 2010).

The discussion about the importance of the timing of soil moisture availability raises the question about how to properly account for the timing of environmental conditions within the season. One basic approach is to adopt weather variables for various seasons of the year. A more recent approach introduced in Ortiz-Bobea et al. (2019) relaxes the additive separability assumption in Schlenker and Roberts (2009a) and allow for the effects of temperature and soil moisture to have non-linear and time-varying effects on crop yields. This implementation is based on a tensor product spline or “bi-dimensional spline” where crop progress within the season and the level of the variable are the two dimensions. I provide details about how to estimate this model in subsection 4.4.

Moving forward, work in this area could focus on ways to improve our understanding of mechanisms through which environmental conditions affect crop yields including farmer management decisions, crop genetics, soil characteristics and their interactions.

3.5 Mixed statistical and biophysical approaches

Perhaps one of the main methodological divides in the literature assessing climate change impacts on agriculture is whether the models are biophysical or statistical in nature. This methodological dichotomy often coincides with disciplinary boundaries and is thus reflected in publishing outlets. One of the major issues with this divide is that it could slow down scientific progress if conclusions from studies based on alternative approaches are perceived as being biased due to the underlying methods used.

To explore this question, Lobell and Asseng (2017) conducted a systematic review of the existing literature to compare prediction of climate change impacts from both biophysical and statistical approaches. The main conclusion is that when studies follow best practices in their respective literature, these methods point to impacts that are largely similar. This means that the previously held perception that statistical model tend to be too “pessimistic” is not really supported by the existing literature. In a somewhat related study Moore et al. (2017) find that the differences between biophysical and empirical studies is small when CO2 fertilization is controlled for.

Recent studies have also started to compare or even combine biophysical and statistical crop yields models. For instance, Roberts et al. (2017) conduct a comparison of a statis-
tical model and a process-based model and find that a combined “hybrid” model tends to outperform individual models in terms of prediction. In addition, that hybrid model tends to point to projected impacts of climate change that fall in between those of the individual approaches.

One key advantage of conducting similar analyses based on alternative approaches within the same study is to better characterize model uncertainty. For instance, Liu et al. (2016) show that both biophysical and empirical models point to similar temperature responses on global wheat yield. This helps address common criticisms from reviewers coming from one specific “camp” of the methodological divide.

Perhaps a fruitful direction of research in this area is the integration of statistical analyses within broader inter-comparison projects like AgMIP. There is indeed a great deal of cross-fertilization that could occur across these different methods. These efforts help bridge the divide across disciplines by seeing these approaches as complementary rather than substitutes.

3.6 Joint estimation of short and long run responses

One of the central methodological dilemmas in the literature relates to the estimation of either short run or long run estimates of climate change impacts. While the Ricardian approach conceptually captures long-run adjustments by assuming farmers are already adapted to their local climate, the approach remains vulnerable to time-invariant omitted variables. On the other hand, panel approaches control for time-invariant unobservables, but are generally perceived as only being able to capture within-season short-run responses to weather fluctuations, and thus unable to capture longer-run adjustments to a changing climate.

However, recent research efforts have sought to combine certain elements of cross-sectional and panel approaches to jointly estimate short and long run responses. For instance, Moore and Lobell (2014) introduce a “hybrid” model to jointly estimate short-run and long-run adaptations to weather fluctuations and climate variations in European agriculture. The model takes the form:

\[ y_{ijt} = \beta_1 \bar{W}_{ijt} + \beta_2 \bar{W}_{ijt}^2 + \beta_3 (W_{ijt} - \bar{W}_{ijt})^2 + \beta_4 X_{ijt} + \phi_j(t) + \alpha_j + \epsilon_{ijt} \]

where \( y_{ijt} \) represents farm profits or yield in region \( i \), country \( j \) and year \( t \), \( W \) represents weather variables (temperature and precipitation), \( \bar{W} \) represents climate (average of annual weather over the preceding 30 years), \( X \) are control variables, \( \phi_j(t) \) is a country-specific time trend and \( \alpha_j \) is a country fixed effect. This specification primarily harnesses the cross-sectional variation in climate within countries (given there is a country fixed effect and there is
relatively less temporal variation in climate) and the temporal variation in weather anomalies. According to the authors, combining these estimates allows depicting an outer “envelope” describing the long run response function, and a series of short-run response functions that are tangent to the long-run response function when \( W = \bar{W} \). This approach combines both cross-sectional and time-series variation to estimate different parameters. These parameters are subsequently combined to assess short and long run responses. However, note that the cross-sectional estimation is still vulnerable to omitted variables operating within countries.

A different approach consists in trying to harness slow changes in the within dimension of a panel model to detect evidence of adaptation to a changing climate. This is the strategy in [Burke and Emerick (2016)] which applies a “long difference” approach to a panel of crop yields to assess the influence of recent climate trends on changes in the sensitivity of crop yields. The study first posits a standard panel data generating process of the form:

\[
y_{it} = \alpha + \beta_1 z_{it} + \beta_2 z^2_{it} + c_i + \epsilon_{it}
\]

where \( y_{it} \) is crop yield in county \( i \) and year \( t \) and \( z_{it} \) is a weather variable (e.g. temperature). The county fixed effect \( c_i \) captures all time-invariant unobserved factors.

The study argues that this model only captures short run changes on yield. The study then posits that if farmers are adjusting input choices (e.g. crop cultivars) to adapt to recent changes in climate, then this would be reflected in a change in the response function over time that would renders extreme weather less damaging. That, is, the response function would trace out an “outer envelope” that allows for longer term adjustments.

To explore this hypothesis, the study first proposes averaging the model above over a multi-year period \( a \), to obtain a new model of the form \( \bar{y}_{ia} = \beta_1 \bar{z}_{ia} + \beta_2 \bar{z}^2_{ia} + c_i + \bar{\epsilon}_{ia} \) where \( \bar{y}_{ia} \) is average yield over the multi-year period of time \( a \) and \( \bar{z}_{ia} \) is the multi-year average weather over the same period. Defining an analogous equation for a more recent period \( b \), and taking the differences between these equations yields what the authors refer to as the “long difference” model:

\[
\Delta \bar{y}_i = \beta_1 \Delta \bar{z}_i + \beta_2 \Delta \bar{z}^2_i + \epsilon_i
\]

which simplifies to:

\[
\Delta \bar{y}_i = \beta_1 \Delta \bar{z}_i + \beta_2 \Delta \bar{z}^2_i + \epsilon_i
\]

Note that the estimated parameters \( \beta_1 \) and \( \beta_2 \) are the same as those specified in the original equation. In the absence of any adaptation, the parameters in this new model would be identical. However, if farmers are adapting to recent climate trends, then those
parameters would shift to make the response function flatter. Applying this approach to US corn yields, the study finds that the parameters of the “long difference” model as very similar to those of the baseline panel model. The study thus concludes that little adaptation has occurred over several decades.

One should highlight that it is unclear whether farmers perceive recent changes in weather patterns as a permanent shift in climate. One should not generally expect agents to make permanent shifts in production practices in response to transient changes environmental changes. Moreover, note that if farmers are adapting to a changing climate, then the baseline panel model is misspecified as we should expect adaptations to be reflected in the short run response function as well.

It is important to clarify that the idea that panel estimates only capture the short-run response is not entirely correct. In a panel model with location fixed effects estimating a non-linear response to weather fluctuations, which is common practice, the identifying variation stems from within location deviations from the mean of each variable. In locations with higher average values of the weather variables (e.g. warmer or wetter climates), the deviations for the quadratic terms are larger. Effectively, this means that group means, in this case climate, plays a role in the identification. That is, cross-sectional variation plays a role in the identification of weather effects. See McIntosh and Schlenker (2006) for an explanation.

In a key recent study, Mérel and Gammans (2021) show that panel estimates are a weighted average of the short-run and long-run response functions to weather and climate. That study also derives the conditions under which the short-run response approximates the long-run response. Intuitively, the extent to which the panel estimate represents more or less the short or the long-run response function depends on the ratio of the within time-series variation to the cross-sectional variation of the weather variable. If a weather variable exhibits greater degree of variation in the cross-section than in the within dimension, then the response function more closely approximates the long run response function. This means that for small panels with units exhibiting similar climates, the estimated response function represents primarily the short run response function. In contrast, estimating global response functions over a large panel with units with large climatic differences (but relatively smaller within variations) approximates the long-run response function. In a similar spirit, Gammans et al. (2020) propose an approach to recover the global long run response function by harnessing variations across adjacent climates. A limitation of these models is that they apply to a subclass of data generating processes.
3.7 Retrospective climate change impacts

The literature on climate change impacts on the sector has been mostly concerned about future projected impacts. Most studies estimate or calibrate a model based on historical data and make predictions about potential future outcomes under alternative climate scenarios and assumptions about farmer adaptation and agricultural markets. However, anthropogenic forces have already altered the climate system as summarized by the IPCC (Pachauri et al., 2014). Our climate is about 1°C warmer than during pre-industrial period. Given that agriculture is highly climate sensitive, it seems natural that these climate changes may have already affected agricultural production.

The first studies trying to analyze the observed impacts of climate change have overwhelmingly focused on teasing out the effect of recent climate trends on yields of major field crops. Lobell and Field (2007) analyze the relationship between country-level cereal yields and growing season weather. Specifically, the study computes first differences of yields and weather variables to control for slowly changing unobservables over time such as management practices. The study finds that there is a clear negative response of maize, wheat and barley yields to higher temperatures. The study then couples these estimates with observed trends in climate variables (1961-2002) and finds the cumulative impact on crop yield for these 3 crop amounts to 40Mt or $5 billion per year.

In a related study, Lobell et al. (2011) revisits this question and focuses maize, wheat, rice, and soybeans, which represent about 75% of calories that humans consume directly or indirectly. Relative to previous work, the study does a better job at matching weather conditions to the growing season of each crop based on the crop calendar complied in Sacks et al. (2010). Other examples of more regional studies include Nicholls (1997) for Australia, Lobell and Asner (2003) for the US, Tao et al. (2006, 2008) for China, Lobell et al. (2005) for Mexico.

As indicated in Porter et al. (2014), these studies have largely focused on attributing the effect of recent climate trends on crop yields without unpacking the anthropogenic sources of these climate trends. More recently, Ortiz-Boba et al. (2021) coupled an econometric model with counterfactual climate simulations to conclude that anthropogenic climate change has slowed global agricultural productivity growth by about 20% over the 1961-2020 period. This loss is equivalent to losing about 7 years of productivity growth over the same period. The strategy in that study is to first estimate a global panel model regression country-level agricultural TFP on annual weather variables. The scope of the study differs from previous ones because the productivity estimates encompass the entire agricultural sector, and not just crops. The study then links the econometric estimates with weather trajectories for 1961-2020 coming out of climate models from CMIP6 from both a historical run with observed
human emissions (the “historical” experiment) and a historical run without human emissions (the “hist-nat” experiment). This allows to compute the cumulative TFP growth over the sample period under these two scenarios. Taking the difference is thus interpreted as the impact of anthropogenic climate change. One of the caveats in that study is that it does not recover how agricultural TFP would have responded to weather in the counterfactual world.

In a related study focusing on global crop yields, Moore (2020) develops an approach that extends the literature on detection and attribution in climate science to global crop yields. Rather than relying on multiple climate models, the paper relies on multiple runs from a single climate model to characterize the internal variability of the model. The study concludes that the patterns of yield growth observed on maize, wheat and rice production have less than a 10% chance of having arisen in the absence of anthropogenic climate change. Specifically, the study finds that anthropogenic climate change has reduced annual calorie production related to these 3 crops by about 5% per year on average since 1961.

3.8 Statistical crop quality models

The focus on crop yield overlooks the fact that weather conditions can affect crop quality (Soares et al., 2019). A small but growing number of economic studies have analyzed the implication of extreme weather conditions and rising carbon dioxide atmospheric concentrations on crop quality and its potential implication under climate change. These models also exploit longitudinal variation in panel model with fixed effects. What typically differs is the nature of the dependent variable, which can vary greatly across crop quality classification systems and countries. For instance, wheat quality is typically captured by its moisture and protein content as well as its milling and baking qualities. Wheat is graded and classified so aggregate data is typically obtained as the share of output falling into different grading categories. For other grains like rice, the quality characteristics vary substantially across countries reflecting very heterogeneous consumer preferences.

A major obstacle in this area is obtaining comprehensive panel data on crop quality. Most previous research is either based on process-based models (e.g. Erda et al., 2005; Asseng et al., 2019) or on the statistical analysis of quality in relatively small samples (e.g. Rao et al., 1993). The economics literature in this area is relatively thin but differs from agronomic research which focuses on direct physical effects on quality. On the other hand, economic studies tend to focus on tradeoffs between quality and quantity or seek to quantify the relative contribution of yield and quality changes on farmer revenues.

For instance, Kawasaki and Uchida (2016) explores the effect of extreme weather on rice yields and quality in Japan. The study finds that while high temperature improves yield,
it also reduces rice quality, leading to an overall negative effect on farmer profits. While most economic research has focused on cereal crops, there is some limited work on fruits and vegetables. Dalhaus et al. (2020) explores the effect of temperature on apple yields and quality in Switzerland. The study finds that the detrimental quality effects of spring frosts can be substantial and can play a larger contribution to farmer revenue than yield effects. Relatedly, some research has focused on wine quality (Erda et al. 2005; Ashenfelter and Storchmann, 2010, 2016).

Moving forward, there is much to be learned regarding the impact of anthropogenic climate change on crop quality. One of the main obstacles seems the availability of reliable longitudinal datasets. This will require new efforts of data collection or partnerships to track quality to better understand the ongoing processes. There is also limited understanding of how climate change may affect micro-nutrient availability, which are critical for small scale farmers who primarily rely on their own production for subsistence. Greater emphasis on how post-harvest management and climatic conditions affect quality is also needed.

3.9 Modeling planting and harvesting decisions

A growing season for annual crops is essentially determined by the time ranging from planting to maturation or harvest. The decision of which crop or cultivar to plant, and when, is critical for agricultural production. For instance, in moisture-limited regions with highly seasonal rainfall, planting prior to the arrival of the first rainfall events could lead to plant death which would require new planting. A similar constraint exists in temperature areas when planting too early in the spring, when the increased risk of frost can jeopardize crop emergence.

In addition, the timing of planting and the choice of the crop cultivar largely determines the timing of when specific stages of plant growth occur during the calendar year. Planting a long-season cultivar in a region with a short season could mean that the crop would not reach maturity during the usual harvest period, which can be problematic. For instance, fall frost can damage the crop in temperature regions. Importantly, the flowering period which tends to occur around the middle of the growing season for annual crop can be particularly vulnerable to heat and moisture stress (Fageria et al. 2006).

Farmers have formed expectations about climate which guides the choices about planting (crop and cultivar choice as well as timing) before the weather conditions unfold throughout the growing season. This is well known but there is relatively little research in economics regarding how farmers form expectations that guide the nature and timing of planting decisions. Changes in the length of the growing season are likely important channels through which climate change will affect farmers. For instance, the expansion of the frost-free period
in temperate regions may expand growing seasons allowing farmers to grow longer season crops and cultivars of giving farmers more flexibility with their planting dates (Ortiz-Bobea and Just, 2013).

While the the current spatial distribution and drivers of planting dates for major crops has been characterized (Sacks et al., 2010), less is known about how farmers are adjusting their practices in response to a changing climate. There is evidence of a multi-decadal trend toward earlier planting in US Midwest that appears beneficial to crop yields (Kucharik, 2006, 2008). However, it is still unclear whether these trends are primarily driven by new cold-resistant varieties or by climate trends.

In addition, climate change is also increasing the intensive and variability of rainfall events, which could lead to excessive moisture during parts of this could be detrimental. For instance, excessive rain in the Spring reduces the ability of heavy farming equipment to enter fields without causing severe soil compaction, which is detrimental to root development and causes long term damage to crop yields (Hamza and Anderson, 2005). These events can be extremely disruptive as the US floods in the Spring of 1993 and 2019 exemplified.

More generally, the influence of weather shocks and climate on the decision of what and when to plant remains under-explored. We still need a more systematic understanding of the potential barriers precluding farmers from making optimal decisions in a changing climate. This is particularly critical in the context of perennial crops such as fruits trees and vineyards where planting is extremely costly and affects farming performance for many years or decades. For instance, it is still unclear whether farmers have begun to shift crops or varieties in specifically in response to climate change and what types of information they rely upon for making these decisions. For instance, would farmers presented with information about recent and projected trends in their locale chose different cultivars of a perennial crop?

The discussion so far has primarily focused on planting. However, the decision of whether to even harvest is also important. Crop abandonment occurs when farmers decide not to harvest a crop they previously planted. Conceptually, this occurs when the cost of harvesting exceeds its expected benefits. Expected benefits depend on yield and output price (as well as any form of production-based government subsidy). Harvesting cost depends on input prices such as fuel and are not necessarily proportional to yield in the case of field crops. One can also factor in the cost of post-harvest management and storage as part of this harvest cost. There are numerous reasons why expected benefits might be lower than harvesting costs. It could be that either yield or output prices are considerably lower at harvest time than the farmer anticipated at planting. It is also possible that harvesting costs become unexpectedly high, which might happen in the presence of an unexpected disruption to labor necessary for harvest (e.g. sudden immigration policy or shock that restricts access to the labor supply).
When these crop abandonment decisions are driven by unexpected drops in yield, say from unusual weather, it is not uncommon to refer to the situation as “crop failure”. Note that crop failure is the result of an economic decision and not a physiological or agronomic condition. The decision not to harvest a crop is inherently economic in nature. One could easily envision a farmer deciding to harvest a crop with extremely low yields if there is a sufficiently high output price.

The literature on climate-induced crop abandonment or failure is relatively thin. The first economics study on this question seems to be Mendelsohn (2007), where a Ricardian-style cross-sectional model is estimated to predict average crop failure rates in the US context. The study relies on reported crop failure rates at the county level based on 5 years of data from the US Census of Agriculture collected from 1978 to 1997. The study finds that about 39% of the cross-sectional variation in crop failure can be explained by soils and climate.

More recently, and using longitudinal variation in a panel, Cui (2020) explores how weather shocks not only influences US crop yields but also the fraction of planted acres farmers end up harvesting. As with other panel studies, it is unclear to what extent these historical relationships can be extrapolated in the long run under climate change. More research is certainly needed to understand the heterogeneity in crop abandonment decisions and how it is influenced by other sources of risk (e.g. crop and storage prices) and risk management strategies (e.g. crop insurance).

So far the discussion has focused on planting and harvesting decisions surrounding a single season. However, many regions of the world have one or more seasons for the same or different annual crops (Siebert et al., 2010). The number of harvest per year is also referred to as cropping frequency or intensity. Areas with more than one harvest per year tend to be located in warmer regions with sufficient precipitation to sustain multiple seasons.

This is an area that has received considerably more attention by natural scientists than economists. Crop intensity has received growing attention because of its potential to increase global crop production without expanding croplands (Ray and Foley, 2013; Wu et al., 2018) although recent work indicates limited room for increasing cropping intensity (Waha et al., 2020). A particular focus is how climate change could affect the cropping intensity. Using a biophysical modeling approach, Seifert and Lobell (2015) find that the area suitable for the most common form of double cropping in the US (winter wheat followed by soybeans) rose by 28% from 1988 to 2012. The study also finds that the suitable area could double or triple depending on the future climate scenario.

Naturally, a rise in suitable area does not imply that actual area under double cropping will increase given that changes in cropping intensity affects yields (Challinor et al., 2015). Moreover, there is a large discrepancy between the area suitable for double cropping and
the area currently under double cropping suggesting that there are other constraints farmers faced that have not yet been well documented. Gammans et al. (2019) develop an empirical model based on observed double cropping area in the US to assess potential expansion of agricultural production under a warming climate. Climate change is likely to play a key role in driving changes in cropping intensity (Iizumi and Ramankutty 2015; Cohn et al. 2016).

3.10 Irrigation and other input adjustments

Water is an essential input in crop production. Farmers can obtain water via precipitation, but also from irrigation water coming surface or underground sources such as rivers, lakes or underground aquifers. Irrigation has played a fundamental role in the development of agriculture of many nations, including the US (Edwards and Smith 2018). The main emphasis in the economics literature on climate change and agriculture relate to 1- the role of irrigation in explaining how farmers cope with environmental change, and 2- understanding the sources, consequences and solutions to irrigation water misallocation.

Irrigation consists in 1- moving water from a source (e.g. river, lake, aquifer) on or close to an agricultural field, and then 2- applying that water throughout the field where it can reach the root system of crops. The first point relates to the water source (surface or groundwater). The second point relates to the irrigation technology (flood, sprinkler, drip, etc.). Surface irrigation typically requires major infrastructure to manage water flow from the source to the field. That includes canals and water holding infrastructure like dams or reservoirs. This infrastructure investments are substantial so they can require collection action from an association or government. Groundwater irrigation from an aquifer requires drilling and using a pump. It does not require the type of common infrastructure to transport water over potentially long distances like surface water irrigation.

A fundamental point is that having access to water via irrigation fundamentally changes how farmers cope with changing climatic conditions. For instance, Ortiz-Bobea et al. (2018) shows that agriculture is much more sensitive to weather fluctuations in the Eastern parts of the US than in the mostly irrigated Western regions of the country. This points relates to an early debate regarding the role of irrigation in the Ricardian literature. In Mendelsohn et al. (1994), the hedonic model did not include an irrigation variable in the cross-sectional regression. Darwin (1999) pointed this out and proposed an alternative model with irrigation as an additional variable. However, water from irrigation is not separable from other climatic inputs. Empirically, this means that irrigation and climatic variables interact, so that the marginal effect of weather on agricultural outcomes depends on irrigation. In addition, and as pointed out in Schlenker et al. (2005), irrigation water is often subsidized in the US.
and its long term availability is uncertain, so performing a Ricardian model over irrigated areas to make long term inferences about climate change impacts can be misleading. As a result, Schlenker and Roberts (2006) propose a Ricardian model focused on the mostly rainfed Eastern parts of the country. Focusing on the Eastern US and non-irrigated areas has become a common sample restriction in order to avoid the complex issues surrounding irrigation.

There seems to be three major factors that complicate the long term analysis of irrigation in a changing climate. First, irrigation infrastructure (e.g. canals, dams, etc.) is often subsidized and water is typically supplied to agricultural users below its cost of provision. Understanding the long term implication of irrigation for the agricultural sector requires understanding these true costs, but obtaining that data is difficult. One of the implications is that farmers may treat water as an abundant resource, and therefore not invest in irrigation technologies that conserve water.

The second complicating factor are water rights. The rules surrounding how water is allocated between agricultural users and between agricultural and non-agricultural users can be highly complex and vary considerably by region. In the US context, water in the Western US is governed by a prior appropriation doctrine (first users to claim water have priority) whereas water rights in the Eastern US follow riparian rights (users close to the water source have priority). There are also important issues regarding the common pool nature of groundwater resources and the potentially perverse incentives that arise that may lead to more rapid water depletion.

The third complicating factor is the future availability of water, especially in a changing climate (Elliott et al., 2014). In the case of aquifers with slow natural recharge (e.g. Central Plains aquifer in the US), the use of water is akin to mining a non-renewable resource. But in other aquifers the dynamics of recharge and the interactions with surface water systems make projections future water availability highly uncertain. A warming climate will also increase evaporative demand, placing new constraints on water availability for irrigation (Fischer et al., 2007). Also, surface water supply is linked to precipitation in a watershed, so the future availability of water for irrigation at a given location may depend on the water cycle in potentially distant locations. This is particularly the case in agricultural regions that depend on water from recurrent glacier melt such as in the Indus, Ganges and Brahmaputra river basins. But these complicating factors do not preclude to research documenting the nature of farmer adjustments to changing environmental conditions over historical periods.

Indeed, an important direction of research documents how farmers adapt to changing water scarcity. For instance, Hornbeck and Keskin (2014) explore the advent of groundwater irrigation in US Central Plains following the Second World War. A key characteristic of this
region is the presence of one of the largest groundwater aquifers in the world, which was previously inaccessible to farmers with pre-war technology. The study analyzes how agricultural production evolved on either side of the aquifer boundary. The study shows how counties with access to the aquifer first became more resilient to droughts, but then progressively specialized in more water-intensive crops which in turn increased drought sensitivity. Counties without access to the aquifer maintained drought-resilient agricultural systems. In a related study, Hornbeck (2012) explores the long term impact of the American Dust Bowl and analyzes, among other things, the role of irrigation in helping farmers cope with an unprecedented environmental disaster and drought.

A more recent example includes Hagerty (2020), which relies on high-resolution land cover data in California to derive short and long run changes in farmer cropping choices over time in response to changes in water availability. The paper exploits changes in institutional settings that lead certain farmers to have more water than others. This type of work requires detailed institutional knowledge of water allocation arrangements and regulations. In a related study, Arellano-Gonzalez and Moore (2020) show that access to a groundwater banking project decreased drought risk, which in turn increased the farming transition from lower-value annual crops to higher-value perennial nut crops in California.

Research has also focused on credibly teasing out the value of irrigation water to farmers. These valuation models consist in hedonic models where access to irrigation water is one of the features of the land. The rising availability of repeated sales data now allows the estimation of panel models with parcel or location fixed effects which allows the more credible identification of these values relative to cross-sectional designs (Buck et al., 2014; Mukherjee and Schwabe, 2015).

There is also a growing literature exploring the role of irrigation in helping stabilize agricultural production and thus prevent conflict. For instance, Gatti et al. (2021) find that irrigation infrastructure can help mitigate the effect of growing-season rainfall shocks on conflict in Indonesia.

The rise of smart technologies are also providing access to new datasets to track farmer behavior in ways that were impossible before. For instance, Christian et al. (2021) track high frequency data on water use in Mozambique and find what appear like inefficiencies in farmer decisions. The study then introduces a randomized control trial providing information aimed at improving farmer water management. Field studies like appear promising in helping enhance farmers decisions about water allocations in a changing climate.
3.11 Market equilibrium and trade

Most of the discussion so far has focused on direct impacts of extreme weather or climate change on agricultural production without any particular consideration to market equilibrium and price formation. Climate change is not a localized idiosyncratic shock, but a shift that affects virtually every economic agent in the world. As a result, domestic and international trade and markets are likely going to play a central role in modulating how climate change impacts are distributed within and across nations.

One of the earliest studies to endogenize prices in a country-level context is [Adams et al. (1990)]. In that study, the authors linked biophysical process-based crop models with a partial equilibrium market model. While the goal of the crop model is to translate changes in climate into changes in agricultural productivity, the role of the economic model is endogeneously determine prices and quantities produced in the agricultural sector. However, these are partial equilibrium models where some features of the global economy are considered exogenous (e.g. demand for food, incomes, etc). Other examples based on partial equilibrium models include [Adams et al. (1995), Reilly et al. (2003) and Janssens et al. (2020)].

It was perhaps [Rosenzweig and Parry (1994)] that first introduced a general equilibrium framework to the analysis of climate change impacts on world food production. In that study, the authors linked biophysical crop models with national agricultural sector models in an overall framework representing all economic sectors with endogenous supply and demand. More recent work in this area relies on the Global Trade Analysis Project or GTAP (e.g. Randhir and Hertel 2000, Hertel et al. 2010, Baldos and Hertel, 2014 and Moore et al., 2017). For a guide to general equilibrium modeling in agriculture see [Hertel (2013)].

In a large comparative study, [Nelson et al. (2014)] contrast how nine global economic models influence estimates of climate change impacts when subjected to standardized yield impacts. Among the economic models, they consider both partial and general equilibrium models. They find that the largest differences coming out across these economic models are in terms of responses in agricultural production, cropland area, trade, and prices. They find that these differences originate from model structure and specification. In particular they find that the ability to convert land to agriculture, to intensify agricultural production and the propensity to trade are some of the most critical factors in these models. It appears that there are still important uncertainties related to the role of these market forces in modulating climate change impacts.

In a recent study, [Costinot et al. (2016)] propose a general equilibrium framework based on micro level data from 1.7 million agricultural fields to explore the role of trade and within country reallocations in modulating the effects of climate change on global agricultural welfare. A key contribution is the ability to consider a large number of fields within countries
that allows analyzing adjustments both within and across countries. The study finds that changing comparative advantage will drive crop substitution within countries which will greatly reduce climate change impacts. They find that climate change would reduce global GDP by about 0.26 percent, which is about one sixth of total crop value. Perhaps surprisingly, they find trade adjustments would play a very little role in explaining the magnitude of this result.

More recently, Gouel and Laborde (2021) revisit this work and find drastically different results. They find that international trade plays a comparable role to within-country crop reallocation. It appears that the main critical factor explaining the differences is the choice of the counterfactual. In Costinot et al. (2016), the authors appear to constrain the export shares to remain unchanged under climate change. Instead, constraining bilateral import shares to remain the same yields a much larger role for trade. Interestingly, this new study finds large regional heterogeneities in impacts with large losses for net-food-importing countries and benefits for agricultural-exporting countries due to more favorable terms of trade.

I should highlight that the trade literature has most closely developed in tandem with biophysical crop process-based models. The interactions with the empirical literature based on statistical and econometric models remains limited. It seems like greater collaboration and integration accompanied by systematic model comparisons are needed to resolve ongoing debates.

### 3.12 Understudied problems and unsettled questions

Here I discuss problems in the literature that seem understudied or that remain unsettled. This list is by no means exhaustive and reflects my own preferences as a researcher.

One of our roles as researchers is to identify mechanisms and policies that could enhance adaptation to a changing climate. This includes identifying institutional barriers to adaptation. For instance, governments pay billions of dollars in subsidies every year to farmers. Some governments have also implemented major policies that create sizable non-food markets for agricultural products, such as the Renewable Fuel Standard in the US. However, the effect of farm policies in enhancing or hampering adaptation to climate change remains largely unexplored. Ortiz-Bobea et al. (2018) finds that certain US agricultural regions are growing increasingly sensitive to rising temperatures and this is partly due to regional specialization. The role that policies and trade have played in this remains unclear but seems plausible. There may also be unintended consequences to large government programs. For instance, Annan and Schlenker (2015) find some indications that crop insurance could
provide a disincentive to adapt to extreme temperatures.

Perhaps one of the most understudied issues pertaining to agriculture and climate change is climate justice. A lot of the global work has emphasized inequities in terms of cross-country impacts. But more research is needed to understand inequities within countries and how these are potentially exacerbated by existing socio-political systems that perpetuate social exclusion.

Another area that has received little attention is the economics of research and development (R&D) and innovation in a changing climate. The literatures on R&D and climate change have evolved mostly separately and the time is ripe for integration and collaborations between these fields. This is critical, because agricultural innovations are for the most part developed outside the farm and they are not easily transferable across bio-climatic zones. In addition, the returns to R&D take years if not decades to materialize and climate is rapidly changing. Are current global and regional investments and infrastructure adequate under a changing climate? There is also no research on the potential role of the private sector in the R&D ecosystem under climate change.

An environmental challenge that is likely to become more prevalent in a warming climate is soil salinity. Soil salinity arises from salt water intrusion in low-lying agricultural coastal areas (e.g. Bengal region) or from the evaporation of large quantities of irrigation water. Soil salinity is toxic for many cultivated plants which negatively affect yields. Breeding or planting salinity-tolerant crops likely imposes a cost to farmers in these areas. For instance, Finkelshtain et al. (2020) recently analyzed the substitutability between freshwater and non-freshwater sources in irrigation in Israel. More research on these matters under climate change are needed and will likely require inter-disciplinary collaboration with non-economists to better characterize the process of water salinization in the future.

Researchers have allocated considerable effort to understanding a few things very well. However, we still have a rudimentary understanding on very important matters. For instance, we know relatively little about the impacts of climate change on agricultural labor. There are a few studies analyzing how weather shocks affect the labor supply. For instance, Branco and Féres (2020) find that droughts tend to increase the labor supply of rural households in non-agricultural sector in Brazil. Some studies are also exploring how heat is affecting human capital accumulation and the role that agriculture plays (Garg et al., 2020). But more research is needed in this under-explored area.

Overall, there is much more emphasis on agricultural production and in agricultural fields, and less on what happens afterwards or beforehand. For instance, there is less research on how weather can affect food quality and post harvesting processing and associated crop losses. Similarly, there is little understanding of the robustness of food and agricultural
supply chains.

We also have a limited understanding of how changing pest pressures linked to changing biodiversity would affect agriculture. This is particularly challenging because observational studies based on panel data might not be necessarily well suited for such analysis. For instance, a warm year does not lead to the same pest pressure than an equally warmer climate would induce. There are not only farmer adaptations to consider, but also ecological adjustments that remain largely unknown. This invites a greater degree of collaboration and integration with ecologists and other natural scientists.

Finally, economists have for the most part favored working on observational empirical studies in isolation. However, there are fruitful collaborations that can arise from closer integration with crop scientists, particularly in the context large inter-comparison projects such as AgMIP. These collaboration can lead to major publications in interdisciplinary outlets that could have greater impact on policy than what economists can do on their own.

4 Coding and other empirical matters

The analysis of climate change impacts and adaptation in agriculture involves specialized knowledge and training that is generally not offered in graduate programs in economics, agricultural and resource economics or other related fields. For instance, conducting empirical research in this area requires manipulating large geospatial datasets (e.g. weather data) which are more common currency in environmental sciences than in economics. Unfortunately, this deficit in training means that new researchers to this field often face substantial barriers to entry.

This section provides a hands-on introduction to common tasks in this area of research in an attempt to cover this “hidden curriculum”. Increasingly, these tasks are carried out in open-source programming languages like R, which allows the flexible integration of workflow from the manipulation of geospatial data to the regression analysis with the ability to produce high-quality visualizations. This integration also facilitates the reproducibility and replicability of research projects. This is critical as a growing number of academic journals require that papers be fully reproducible.

The section provides a rationale behind how to code these tasks, but also provides code and data to fully carry out these tasks, including the ability to reproduce the figures in the chapter. The reproduction code and data are hosted in a permanent repository at the Cornell Institute for Social and Economic Research (CISER) at Cornell University (https://doi.org/10.6077/fbla-c376).
4.1 Aggregation of point weather data

As indicated in section 2, the most basic form of weather data comes from weather stations. These are point datasets where weather observations are geo-referenced. Relying on these direct observations may seem appealing but they present some clear challenges for the non-specialist. The first inconvenience is that the spatial distribution of weather stations may be sparse (see Fig. 1). This means that the researcher may not be able to accurately obtain weather information in the precise locality under study. The second issue is that weather data are not always quality-controlled. That means that the researcher needs to spend considerable effort “cleaning” the data for suspicious or implausible outliers. The third challenge is that weather observations may be missing in some time periods. These issues of sparsity, data quality and attribution, pose empirical challenges related to measurement error and attrition bias which have important econometric consequences.

In cases when all units of observations are very close to weather stations, say in the example of geo-referenced farm-level data, it makes sense to rely on the closest weather station data. In cases when the researcher is interested in weather conditions that fall between weather stations, some form of interpolation may be necessary. The most basic type of interpolation is an inverse-distance weighting approach.

Performing your own interpolations, however, is generally not ideal. There are numerous high-quality datasets created by meteorologists and climate scientists based on sophisticated interpolations or other model based approaches (e.g. interpolation accounting for orography or reanalysis). Those third-party products typically implement cutting-edge approaches and undergo careful quality control procedures by dedicated trained professionals. Trying to replicate similar work for an economic research project is risky because these procedures are error-prone. Readers and reviewers are rightfully skeptical of whether the researchers were able to perform interpolation adequately. This requires researchers to allocate non-negligible amount of effort describing and validating their interpolation approach.

The comparative advantage of economists does not lie on environmental data interpolation. We are thus generally better off relying on datasets developed by climate scientists unless there is a strong reason not to do so. For instance, performing one’s own interpolation may be justified for study regions where existing gridded datasets have been found to be unreliable.

In the accompanying R code and data, I provide a simple introduction to basic forms of spatial interpolation (see 1_weather_data.R). To illustrate these techniques I rely on weather station data from the GHCN database falling over the lower 48 US states. I also select maximum temperature (Tmax) on August 16, 2020 as the example. Figure 3A shows Tmax on that day over more than 6,000 weather stations across the US. We can see some
regions of the country have a relatively sparse network of weather stations.

Suppose we are interested in creating a county-level dataset based on these weather stations. This means converting these 6,000 station-level observations to a little more than 3,000 counties. Perhaps the most basic type of mapping is to simply assign to a county the value of the weather station that is nearest to the centroid of a county. This is precisely what is shown in Fig. 3B. This approach may work better in areas with homogeneous landscapes and no mountain ranges. But this approach fully reflects any local noise stemming from a particular weather station.

An alternative approach is to perform a weighted average of nearby weather stations. Figure 3C shows this procedure for the \( k \) nearest stations to a county’s centroid (with \( k = 5 \)). In computing these weighted averages, the weights are proportional to the inverse of the distance to the county’s centroid. This way stations that are closer to the county are weighted more heavily. Naturally, these weights must add to unity. This approach smooth out local noise from any particular weather station. The downside, obviously, is that it may smooth out temperature too much, especially over location with major spatial climatic differences over short distances (e.g. California). In addition, this approach may be problematic if weather stations are extremely sparse. In such cases this approach could potentially over-smooth weather conditions. One potential fix is to reduce the number \( k \) of neighboring stations used in the interpolation. In general, this approach appears more suitable to situations with relatively dense or homogeneous network of weather stations.

In other contexts, relying on all the weather stations within a certain distance of a county could be preferable. That is the strategy used in generating Fig. 3D. In that interpolation, I chose all stations within 1° (~111 km) and relied on an inverse-distance weight. This procedure may be appropriate when the station distribution is highly sparse and heterogeneous. If the distance cutoff is too large, this approach may also over-smooth weather conditions in regions with contrasting climates over short distances (e.g. California). However, setting a distance cutoff that is too small may lead to missing observations if station density is sparse in certain parts of the study region.

I should note that interpolating temperature variables is prone to smaller errors than precipitation. Temperature is a smoother field and is more amenable to these procedures. Precipitation, on the other hand, is spatially discontinuous, particularly at finer temporal scales (e.g. daily), so interpolation can introduce substantial error at fine spatial scales.

In some circumstances a researcher might be interested in harnessing high spatial resolution from one dataset with the higher temporal resolution of another. For instance, the PRISM data is available at a daily scale starting in 1981. But the monthly PRISM data starts in 1896. What if we were interested in deriving a daily PRISM-like dataset prior to
Notes: All maps show maximum temperature (Tmax) on August 16 of 2020. A: Tmax over 6,785 weather stations from the GHCN database falling over CONUS. B: Assigns value of weather station closest to a county’s centroid. C: Inverse-distance spatial interpolation based on the 5 nearest stations to the county’s centroid. D: Inverse distance interpolation based on stations located within 1° of the a county’s centroid.

Figure 3: Spatial interpolation of weather station data.
1981 based on the PRISM grid? That is precisely what Schlenker and Roberts (2009a) did, where they harnessed the high spatial resolution of the monthly PRISM data over 1950-2005, and combined with with daily weather station data over the same period. Their goal was to derive the daily distribution of temperature at the fine spatial scale of the PRISM grid.

Here I illustrate how to do this for daily maximum temperature (Tmax) and precipitation (ppt) using the monthly 4-km dataset from PRISM and daily but relatively sparse weather station data from the GHCN database. I focus our attention on weather conditions over CONUS for August 16, 2020 and present the procedure step by step.

The first step is to interpolate daily weather station to the PRISM grid. The goal of this step is to “infuse” the PRISM grid cells with the temporal variation from the weather station data. Note that the PRISM grid has 872,505 cells of which 481,631 fall over land, whereas the GHCN database has maximum temperature data for 6,028 stations and precipitation data for 14,492 stations. This means that this interpolation has a larger “target” dataset (PRISM grid) than the “source” dataset (stations). This will expectedly lead to fairly smoothed out patterns at a very fine scale and might not respect fine-scale spatial differences arising due to orography or proximity to the coasts. Specifically, I select the 5 nearest weather stations for each PRISM grid cell and compute an inverse-distance weighted average of each variable. This is repeated for each PRISM grid cell, noting that the weather station population varies by variable. This step leads to 31 daily interpolated layers for each variable for the month of August of 2020.

The second step consists in ensuring that the daily interpolated PRISM data are consistent with the monthly PRISM data. That is, we constrain the daily data so that when aggregated it matches exactly the monthly PRISM data. To do this for temperature, I start by subtracting monthly average from the daily interpolated data layers. Essentially, this only leaves the local anomalies in the interpolated data. I then proceed to add the monthly average from the reference PRISM grid to these daily interpolated anomalies. This reference monthly file has a finer and more accurate rendering of spatial climatic differences. For precipitation, I scale the daily precipitation variables based on the ratio of the total precipitation from the daily interpolated files and the reference monthly PRISM data layer. This procedure ensures that I do not create “ghost” rainfall in places and days where it did not rain.

I summarize the results of this interpolation in figure 4. Fig. 4A shows the resulting interpolated maximum temperature for August 16, 2020. Notice that this interpolation technique preserves very fine-scale spatial variation close to mountains and coasts. As previously mentioned, PRISM provides daily data since 1981 so we can contrast our interpolation with

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4The weather stations counts concern balanced weather stations for the month of August of 2020.
Notes: All maps show maximum temperature (Tmax) on August 16 of 2020. A: Tmax over 3,431 weather stations from the GHCN database. B-C: Inverse-distance spatial interpolation based on the stations located within 0.5 and 1° of the each county’s centroid. D: Inverse-distance interpolation based on the 5 nearest stations to each county’s centroid.

Figure 4: Spatial interpolation of weather station data.
their\textquotesingle; shown in panel B. The spatial patterns are very similar, but not identical as indicated in panel C showing the difference between panels A and B. The PRISM team likely operates a more sophisticated technique than what I employ here.

Figure 4D shows the interpolation for daily precipitation for the same day. The spatial patterns of precipitation appear slightly less realistic than the daily PRISM data shown in panel E, but the differences are surprisingly small as indicated in panel F. However, note that differences can be very large (e.g. shows rain in panel D and no rain in panel E) in certain places due to differences in interpolation techniques.

While simple interpolation techniques like this appear to work, I invite the reader to exhibit extreme caution when performing these calculations. The output from these procedures is not validated which means that we have a very limited understanding of the type of the underlying measurement error. Advanced users are invited to seek additional resources in kriging and more advanced geospatial statistic tools.

4.2 Aggregation of gridded weather data

Here we turn our attention on how to efficiently aggregate gridded weather data by administrative units (e.g. counties). As discussed in section 2.3, gridded or raster data are matrices with data on a particular variable (e.g. precipitation) linked to information on how the cells of the matrix map into space and time. These are essentially geographically and temporally referenced matrices. This characterization is important because it means that manipulating such data can be greatly improved by relying on matrix algebra which are performed efficiently by programming software like R. Weather raster files can come in a variety of formats but perhaps the most common is NetCDF. These are typically multi-layer raster files in which each layer corresponds to a time period. For instance, it is common to see daily weather datasets provided as multi-layer annual files (1 file with 365 layers).

The way that each grid cell in a raster is mapped into a particular location on Earth is determined by a few parameters, including the extent, spatial resolution, and projection. The extent defines the “boundaries” of the raster. Because rasters are rectangular, the extent is simply a matrix providing information on the southern, northern, western and eastern limits of the raster. These limits are typically provided in degrees (but not always). A global dataset can thus range from -180° W to +180° E, for rasters centered in Europe, and from -180° S to 180°N, although it is rare to see rasters extend to the poles. The spatial resolution of the raster simply indicates the size of a grid cell in degrees, although sometime also in meters. Finally, the projection is the rule by which the surface of the Earth is flatten for the purpose of visualization. Gridded weather datasets are generally “unprojected” using a
simple latitude-longitude (or lat-lon) projection. This portrays the gridded surface of the
earth as a flat rectangle on a computer screen. Importantly, changing the projection of a
raster can be time consuming (at least in R) because the boundaries of each grid cell need to
be reprojected. As a result, it is often preferable to change the re-project polygon data (e.g.
administrative boundaries) to match that of the raster data, and not the other way around.

The key point to efficiently map gridded data to administrative units is to recognize
gridded data as a matrix. A multi-layer raster containing daily information for \( N \) grid cells
and \( T \) time periods can be though of as an \( N \times T \) matrix, which I denote \( G \) (for gridded).
The target aggregated dataset would be a \( n \times T \) matrix, which I denote \( A \) (for aggregated or
administrative). We usually have \( n \ll N \), but not always (more on this later). The “trick”
is to consider the transformation of \( G \) into \( A \) as a matrix multiplication of the form:

\[
A_{n \times T} = P_{n \times N} \times G_{N \times T}
\]

Matrix \( P \) is a transformation or projection matrix that converts the gridded data \( G \) into
aggregate data matrix \( A \). That transformation is simply a weighted average of rows in \( G \)
to obtain aggregate matrix \( A \). To clarify this further, the first row of \( P \) corresponds to the
first administrative unit in the aggregated dataset (e.g. a country, state, county, etc.). The
first column of \( P \) corresponds to the first grid cell in the gridded dataset. Thus the first row
corresponds to a vector of weights for computing a weighted average of grid cells in \( G \) in
order to obtain the data for the first administrative unit, which is located on the first row of
\( A \). Values in each row in \( P \) must add to 1, and only grid cells falling within the administrative
unit should have non-zero positive values.

That means that \( P \) is mostly full of zeros and could be adequately represented as a sparse
matrix on a computer. For a sparse matrix, a computer only holds the values and location
of non-zero values in the memory. This is a memory efficient way of storing large matrices
and for computing fast matrix multiplications.

The projection matrix \( P \) can be created in various ways. Perhaps the most basic ap-
proach is to give equal weight to every grid cell falling within each administrative boundary.
However, as we saw in Fig. 2, giving the same weight to every location within a county or
state may be misleading because it does not convey information about the locations within
the administrative units where the economic activity of interest operates or relies upon. This
is particularly critical for large administrative areas like countries, or large geographically
diverse states, like in the Western parts of the US.

A more common approach of constructing the projection \( P \) matrix is for it to reflect
weights that correspond to areas where relevant economic activities take place. For instance,
in the case of economic studies exploring the effect on overall economic activity, it is common
to see gridded weather data aggregated over areas where population are located within the administrative units. In the case of agriculture, it is common to rely on cropland, or cropland and pastures, as the underlying land cover information to construct such weights. For global studies one can rely on global datasets describing the global distribution of agricultural lands (e.g. Ramankutty et al., 2008). For more regional studies, one can rely on finer scale land cover datasets. In the US context, it is common to rely on either the USDA NASS Cropland Data Layer (CDL) or USGS National Land Cover DataBase (NLCD). The CDL is an annual product with 30m resolution and is differentiated by crop. The NLCD is also 30m but has broad land cover categories as it pertains to agriculture (e.g. cropland or pasture).

The advantage of performing spatial aggregation in this manner is that the researcher only needs to compute $P$ once. Matrix $P$ is essentially a matrix of aggregation weights. The spatial aggregation can be done in a fraction of a second by performing the matrix multiplication above because these matrix operations can be done very fast with current computers. The main bottleneck in the spatial aggregation is reading matrix $G$ into the memory and perhaps writing matrix $A$ to the disk. This workflow presents a substantial gain in speed when aggregating very large datasets with either high spatial or temporal resolution. The alternative typically consists of using canned functions that perform overlays of raster and polygons for each raster layer. Such strategies have a substantial overhead that make the rapid aggregation of large datasets infeasible.

The R code included with this chapter provides an illustration of how to compute the matrix $P$ based specific types land cover falling within each US county to aggregate PRISM data (see 1_weather_data.R). The first step is to create a new land cover raster that matches the target PRISM raster grid. This aggregation can be done by computing “zonal statistics” which is simply computing the frequency of small 30m land cover pixels falling within each PRISM grid cell. Fig. 5 shows the fraction of each PRISM grid cell covered by cropland, pasture and grassland. As expected, areas in the Midwest and the Central Plains are mostly allocated to these classes. The second step is to derive a vector of weights that sum to 1 within each county, based on the land cover fractions of the grid cell falling within each county. The third step is to store these aggregation weights in a sparse matrix $P$. The final step is to perform the matrix multiplication to perform the aggregation.

Importantly, note that the interpolation of weather station data described in subsection 4.1 can also be conducted using sparse matrices. In fact, the implementation shown in the R code provided does precisely that. In other words, performing averages of observations over nearby weather stations does not require a loop. Doing a loop would be tremendously inefficient and possibly make the project intractable for large datasets. The aggregations described here are simply linear transformations of matrices, whether the source matrix
Notes: The cropland, pasture and grassland shares are computed based on 30m land cover data from the National Land Cover Database (NLCD) for 2016.

Figure 5: Fraction of cropland, pasture and grassland in each PRISM gridcell. \[\text{\textbf{5}}\]

represents raster or point data, and where the transformation matrix \(P\) is a sparse matrix with aggregation weights.

### 4.3 Estimating non-linear effects

Now that we have covered the basics of how to aggregate weather data to administrative units, I focus our attention to the estimation of nonlinear effects of temperature. Specifically, I illustrate how to estimate the semi-parametric model introduced in Schlenker and Roberts (2009a). Rather than estimating the effect of temperature on crop yields, that study examined the effect of exposure to different levels of temperature on crop yields. I emphasize the term exposure, because the underlying variables in the analysis are actually measures of the amount of time spent at various temperature intervals or “bins”.

The motivation behind this approach is that temporal averaging of temperature conceals the exposure to extreme temperatures. Two temperature sequences may have the exact same average, but one may exhibit considerably more exposure to high temperature. The underlying hypothesis is that exposure to various levels of temperature affect agricultural outcomes (e.g. crop yield) very differently, so capturing the varying effects of exposure to the entire temperature distribution may yield deeper insights.
Notes: The figure represents minimum (Tmin) and maximum (Tmax) temperature data from a random location in the lower 48 states from the PRISM dataset during the month of August of 2020. The grey dots describing a sine curve between consecutive Tmax and Tmin are obtained via interpolation every 15 minutes. Temperature intervals of 1°C are highlighted in dashed lines over the entire month. The green distribution on the right shows the underlying temporal distribution of temperature throughout the month. It is essentially a histogram of the 15-min points that I just described. The distribution adds to the total number of hours (or days) in the month.

Figure 6: Illustration of the construction of temperature bin exposures from daily minimum and maximum temperature.

Capturing such linearities requires information on how much time is spent at each temperature level or “bin”. These bins are typically 1°C wide, ranging from say 0° to 40°C. Intra-daily (e.g. hourly) data is often impossible to obtain in a reliable fashion so deriving these intra-daily distributions often requires making assumptions about the temperature-time path. A common assumption is that temperature follows a sine curve passing between the minimum and the maximum temperature of each day. This naturally requires data on daily minimum and maximum temperature.

The R code provided illustrates how to build exposure data from a sequence of daily minimum and maximum temperature. The results for a random location in the US is shown in Fig. 6. The figure shows the daily sequence of Tmax and Tmin with in red and blue points, respectively. To this I add an interpolated intra-day temperature trajectory. The code
generates a series of points at 15-minute intervals based on a double sine curve that passes through T_{max} and T_{min} of consecutive days. Computing the exposure bins simply consists in determining the frequency of these 15-minute interval points throughout the month. This distribution is shown in green on the right side of the figure. Note that the support of this distribution is time and is measured in hours or days, not °C. The distribution describes how much time is spent in each temperature interval. By construction, summing over all the bins over a month adds to the number of hours or days in that month. Importantly, note that the temperature “bins” described here are not counts of days in which the average temperature falls in a particular interval.

It is important to emphasize that these bins we are discussing are exposure bins. They are not dummy variables that count whether the average temperature fell within a particular bin. That approach would not capture within intra-day variation in temperature. This is a common point of confusion. In addition, note how averaging temperature over time, say over the entire month, would conceal exposure to extreme temperatures within the month.

We can perform the “binning” exercise for all grid cells located over the US and for each month of the year. In the code provided I do this for every month over the 1981–2020 period for bins ranging from −10 to 50°C in 1°C intervals. For each month, the code creates a file with 61 layers (one per bin) corresponding to the amount of time spent in each bin. I illustrate the exposure above 30°C for August of 2020 in Fig. 7. This is essentially showing the sum of all the exposure bins above 30°C in August (depicted for one grid cell in Fig. 6) over all PRISM grid cells. In the map you can appreciate the importance of latitude and orography in explaining cross-sectional differences in temperature exposure. For instance, certain parts of the Southwest experienced more than 720 hours above 30°C. August has 31 days or 744 hours, meaning that some of these regions experienced temperatures above 30°C over virtually every single moment of the month. In contrast, other regions of the country experienced little to no exposure beyond 30°C (dark blue).

Note that these exposure bins for temperature are related to the degree-day concept discussed in subsection 2.5. In fact, degree days can be computed directly from these exposure bins. Specifically, computing degree-days between a low threshold \( h \) and a high threshold \( \bar{h} \) can be written as:

\[
DD_{h \to \bar{h}} = \sum_{k=h}^{\bar{h}-1} z^k \times (\bar{h} - 30 + 1)
\]

where \( z^k \) is the exposure (e.g. in days) to the \( k \)-th temperature bin. For instance, when computing growing degree-days between 8 and 32°C, we would set set \( h = 8 \) and \( \bar{h} = 32 \). When computing “extreme” degree-days, say above 30°C, we would set \( h = 30 \) and \( \bar{h} \) at a very
Notes: The derivation of this exposure relied on daily data from PRISM.

Figure 7: Map of exposure above 30°C in August of 2020.

high level that is never reached (e.g. 60°C). In essence, the expression above approximates the area under the temperature curve and between a lower and an upper threshold.

Now let’s move to how to represent the effect of temperature exposure on crop yield following the approach laid out in Schlenker and Roberts (2009a). The underlying data generating process presented in that study is of the form:

\[ y_{it} = \int g(h)\phi_{it}(h)\,d(h) + p_{it} + p_{it}^2 + \psi(t) + \alpha_i + \epsilon_{it} \]

where \( y_{it} \) is the log of yield in location or county \( i \) and year \( t \), \( p_{it} \) is growing-season precipitation, \( \psi(t) \) is a time trend, \( \alpha_i \) is a county fixed effect and \( \epsilon_{it} \) is the error term. The first term represents the effect of temperature on crop yield, where \( g(h) \) is the marginal effect of temperature \( h \) on yield, and \( \phi_{it}(h) \) is the growing-season density at \( h \) in that location and year. The integral simply means that the product of marginal effect and exposure is summed over the entire temperature range, given that the integrating variable is \( h \). This continuous representation is theoretical and is not tractable for estimation. However, that integral can be approximated in various ways empirically. In the original study, the authors provided 3 ways of approximating this function, using a piece-wise linear function, a step function and a Chebyshev polynomial of degree 8.

In this chapter and in the included R code I illustrate how to estimate these models using
step functions, natural cubic splines, and Chebyshev polynomials (see \texttt{2_nonlinear_effects.R}). I focus on US corn yields for the 1981-2020 period east of the 100th meridian West in order to focus on mostly rainfed counties. I set a growing season ranging from August to September. I also bottom and top code the exposure data so that bins range from 0 to 38°C. This avoid having too little exposure at the tails of the temperature distribution, which makes the estimation noisier.

Perhaps the most basic and intuitive approximation is to use a step function. If the temperature range during the growing season ranges from say 0 to 40°C, then the approximation with eight 5°C steps can be represented as:

\[ y_{it} = \sum_{k=1}^{8} \beta_k z_{it}^k + p_{it} + p_{it}^2 + \psi(t) + \alpha_i + \epsilon_{it} \]

where \( z_{it}^k \) is the amount of time spent in the \( k \)-th step or temperature interval. This means that we essentially estimate separate coefficients for each temperature interval. The regression coefficients are to be interpreted as the effect on yield of spending an additional hour (or day) in that particular bin.

Figure \ref{fig:step_functions} illustrates the marginal effects of models with step functions of different widths. In each panel the blue line represents the estimates for each step together with 95 and 99 percent confidence intervals in blue. The green distribution underneath the response function describes the growing-season temporal distribution of temperature exposure in the sample. By construction, that distribution sums to 183 days between April and September.

The first panel of Fig. \ref{fig:step_functions} shows the response function with 1°C steps. This leads to a fairly noisy response function, particularly toward high levels of temperature. As a result, although the point estimates suggest exposure to temperature above 30°C appear detrimental, these effects are not statistically different from zero. This imprecision likely results from the high degree of collinearity between neighboring bins. Indeed, the time spent on any given year between 31 and 32°C is always very correlated to the time spent between 32 and 33°C, and so on for other bins. This is problematic and thus model like this are better avoided. The role of bin size has also been discussed in Carter et al. (2018).

One natural way to avoid collinearity is to aggregate bins into wider steps or intervals. The second and third panels in Fig. \ref{fig:step_functions} show the response functions for models based on steps that are 3° and 7°C wide, respectively. As expected, the resulting response functions are more precisely estimated. Both model also how that temperature exceeding 30°C are detrimental to corn yield. For instance, the last model indicates that an additional day of exposure to the last bin over the growing season (183 days) reduces crop yield by 0.05 log points, or about 5%. That is a substantial reduction.
Notes: Standard errors are clustered at the state and year level. The data covers US corn yields over the 1981-2020 period east of the 100th meridian West. Precipitation variables were included in the regression but coefficients are not shown. The blue colored bands around the response function corresponds to 95 and 99 percent confidence intervals. The green histogram represents the growing-season of exposure to all temperature bins.

Figure 8: Effects of temperature exposure on corn yields based on step functions of varying widths.

Note that the step function approach assumes that the marginal effects between neighboring steps are unrelated. That is, the model does not impose any structure on how smooth the response function could be, which could render the estimation unnecessarily noisy.

One way to address this is to allow marginal effects to vary smoothly across neighboring temperature bins. This can be implemented with a natural cubic spline or a Chebyshev polynomial. Both of these approaches involve a basis matrix $B$ which is used to project the temperature bins (say $J$ bins) into a smaller space (say of size $K$) and thus reduce dimensionality prior to estimation ($K < J$). That is, we are able to estimate only $K$ parameters to represent the marginal effects of $J$ individual bins.

To illustrate, the basis matrix $B$ of a natural cubic spline with $J$ degrees of freedom evaluated over $K$ temperature bins has $K$ rows and $J$ columns. The basis matrix maps a $nT$-by-$K$ matrix $Z$ of data, with columns representing temperature bin exposures, into a $nT$-by-$J$ matrix $X$ of transformed variables used in the regression analysis. In matrix form, this mapping can be represented as:

$$
X_{nT \times J} = Z_{nT \times K} \times B_{K \times J}
$$

This essentially reduces the underlying binned data with $K$ bins to $J$ regressors. Naturally, we select $J \ll K$ in order to substantially reduce the dimensionality of the temperature space. We can now write the regression model in the following form:
\[ y_{it} = \sum_{j=1}^{J} \sum_{k=1}^{K} (\gamma_j B_j^k z_{it}^k) + p_{it} + p_{it}^2 + \psi(t) + \alpha_i + \epsilon_{it} \]

\[ = \sum_{j=1}^{J} \gamma_j \sum_{k=1}^{K} B_j^k z_{it}^k + p_{it} + p_{it}^2 + \psi(t) + \alpha_i + \epsilon_{it} \]

where \( B_j^k \) is the element in the \( k \)-th row and \( j \)-th column of the basis matrix \( B \). The term \( z_{it}^k \) corresponds to one row (observation \( it \)) and the \( k \)-th column of \( Z \), and \( x_{it}^j \) corresponds to one row (observation \( it \)) and the \( j \)-th column of \( X \). That is, rather than estimating \( K \) separate coefficients for each individual bin \( z^k \), we end up with only \( J \) regressors \( x^j \).

After the estimation, one can recover the marginal effects evaluated at each of the \( K \) bins by pre-multiplying the vector \( \hat{\Gamma} \) (containing the \( J \) estimated coefficients) by the basis matrix:

\[ \hat{\beta}_{K \times 1} = B_{K \times J} \times \hat{\Gamma}_{J \times 1} \]

This operation returns a vector \( \hat{\beta} \) of temperature effects evaluated at each one of the \( K \) original temperature bins in matrix \( Z \). One can also easily derive an estimate of the variance of these temperature effects as follows:

\[ \text{Var}(\hat{\beta})_{K \times K} = B_{K \times J} \times \text{Var}(\hat{\Gamma})_{J \times J} \times B'_{J \times K} \]

Obtaining standard errors for the marginal effects consists in selecting the squared root of the diagonal elements of \( \text{Var}(\hat{\beta}) \).

To fix ideas, I illustrate this estimation technique using cubic natural splines with different degrees of freedom in Fig. 9. Each panel in the top row shows the the columns of the basis matrix \( B \) for splines with 3, 7 and 12 degrees of freedom. With temperature bins defined over the 0 to 38°C, the basis matrices have sizes of \( 39 \times 3 \), \( 39 \times 7 \) and \( 39 \times 12 \), respectively. The top row shows these basis matrices performs linear transformation of neighboring bins that are mapped into a reduced number of regressors. This means that each regressor roughly reflects the effects of fluctuations in temperature exposure occurring in neighboring bins. Importantly, these regressors can be transformed “back” to the original support, as previously mentioned and as illustrated in the second row of the figure.

Each panel in the bottom row of Fig. 9 shows the response functions (the vector \( \hat{\beta} \) derived
Notes: Standard errors are clustered at the state level. The data covers corn yields over 1981-2020 east of the 100th meridian West. Precipitation variables were included in the regression but coefficients are not shown. The blue colored bands around the response function corresponds to 95 and 99 percent confidence intervals. The green histogram represents the growing-season of exposure to all temperature bins.

Figure 9: Effects of temperature on corn yields based on natural cubic splines.
above) along with 95 and 99 percent confidence bands (based on $\text{Var}(\hat{\beta})$) corresponding to these splines with varying degrees of freedom. I also depict the underlying distribution of temperature exposure over the growing season in green.

The first panel of Fig. 9 corresponds to a spline with 3 degrees of freedom. This response function clearly exhibits limited flexibility. This is evident by the symmetric response function shown on the lower left panel. Note, however, how the spline with 7 degrees of freedom allows for a more flexible estimation of the response function. This response function shows that exposure above $30^\circ\text{C}$ are clearly detrimental to crop yields.

Moving to the most flexible specification with 12 degrees of freedom, shows a response function that is a bit more unstable but still shows a distinct pattern where exposure to temperature exceeding $30^\circ\text{C}$ are clearly detrimental. Note that the response function because more imprecise at high levels of temperature. This is likely driven by the high flexibility of the model over a temperature range with relatively little variation.

It is also possible to estimate these temperature effects based on a Chebyschev polynomial. The procedure is very similar to a spline given this strategy also involves a basis matrix. The first row of Fig. 10 shows the columns of the associated basis matrix for Chebyschev polynomials of degree 3, 7 and 12. Unlike for the spline, note that the values are not locally defined. What that means is that each regressor carries information regarding exposure to all bins of the temperature distribution. As a result polynomials tend to be a bit less stable around the extremes than splines. The bottom row of the figure shows the response functions and the underlying distribution of temperature exposure. Similar to the spline, we find that exposure above $30^\circ\text{C}$ appears detrimental to corn yields. Note how allowing too much flexibility in the polynomial lead to much noisier effects around the right tail of the distribution.

Overall, this section shows that allowing too much flexibility in the semi-parametric response function leads to relatively noisy effects at the extreme end of the temperature distribution. We also see that not allowing for enough flexibility tends to understate the effects of extreme temperatures.

I should highlight that there has not been a formal exploration of the advantages of these semi-parametric approaches. These models tend to fit the data better than alternative models based on average temperature. But it is unclear to what extent these approaches could reduce issues related to spatio-temporal aggregation bias.

To conclude, note that an important assumption of the approach presented here is that the effects of temperature exposure are additive throughout the growing season. In other words, the timing of temperature exposure is irrelevant. This obviously contradicts agronomic conventional wisdom stipulating that the timing of weather conditions is particularly
Notes: Standard errors are clustered at the state level. The data covers corn yields over 1981-2020 east of the 100th meridian West. Precipitation variables were included in the regression but coefficients are not shown. The blue colored bands around the response function corresponds to 95 and 99 percent confidence intervals. The green histogram represents the growing-season of exposure to all temperature bins.

Figure 10: Effects of temperature on corn yields based on Chebyshev polynomials.
important for crop yield determination. I now turn to a generalization of this model to allow for time-varying effects within the growing season.

4.4 Estimating within-season varying effects

The timing of environmental conditions plays a critical role in agriculture particularly in crop production (Fageria et al., 2006). In the case of many field crops like cereals and leguminous crops, the ability of plants to store biomass in useful parts of the plant (e.g. grain) is in large part determined by the success of their flowering process. If the flowering process falters, then the plant loses its ability to store biomass in seeds (grain fill). Importantly, flowering is a delicate stage of plant development that is fairly vulnerable to environmental stresses. Flowering also occurs over a relatively short period of time around the middle of the crop cycle in annual crops, meaning that environmental conditions can have drastically different effects throughout the growing season.

So how does this affect the estimation of statistical crop yield models? Most standard statistical yield models do not consider the timing of environmental conditions in great detail. For instance, the models we explored in the previous subsection assume additivity of weather effects on yield. That means that the timing of environmental conditions within the season are irrelevant.

There have been various efforts over the years to account for these within season time-varying effects. The most basic approach is to simply include monthly weather variables for various critical period of the growing season. However, those approaches have been found not to substantially improve model fit or lead to significantly different conclusions than models that assume additivity (e.g. see the appendix in Schlenker and Roberts, 2009b). However, these efforts commonly rely on calendar periods of the year rather than actual stages of crop development (e.g. Gammans et al., 2017).

Perhaps the earliest economic study exploring climate change impacts on crop yields that accounts for biophysical features underlying the non-additivity of weather in the growing season is Kaufmann and Snell (1997). In that study, the authors define weather variables over periods corresponding to crop development stages. Many more studies have adopted this approach. For instance, Ortiz-Bobea and Just (2013) estimates a corn yield model with 3 sub-seasons matching crop stages to analyze the effectiveness of changing planting as an adaptation to rising damages from a warming climate. Another example is Welch et al. (2010) that matches weather conditions to vegetative and ripening phases of rice. In a recent study, Shew et al. (2020) link weather conditions to wheat development stages to analyze variations in sensitivity to extreme heat across cultivars in South Africa.
One potential limitation of previous work is that it assumes that the effects between neighboring portions of the growing season are independent. That is, nothing in the modeling approach allows for marginal effects of weather conditions to vary smoothly within the growing season itself.

To address this limitation, Ortiz-Bobea et al. (2019) introduce a bi-dimensional spline that allows the effects of soil moisture and temperature to vary smoothly in levels and throughout the growing season. This model is akin to a bi-dimensional generalization of the crop yield model presented in the previous subsection. We now not only have exposure bins to various levels of environmental variables, but time within the season also becomes a “bin”. So rather than fitting a spline over a vector of binned exposures, this approach applies a tensor spline to a 2-dimensional set of bins.

That study introduces a conceptual model similar to the following, where crop yield may be differently affected by the distribution of environmental conditions throughout the growing season:

\[
y_{it} = \int \int g(h, p)\phi_{it}(h, p)d(h)d(p) + p_{it} + p_{it}^2 + \psi(t) + \alpha_i + \epsilon_{it}
\]

where \(\phi_{it}(h, p)\) describes the distribution of the environmental variable \(h\) at each level of progress \(p\) in the growing season, and \(g(h, p)\) describes the marginal effect of the environmental variable throughout the season. Although he I only show one environmental variable, the study considers soil moisture and air temperature. The rest of the specification is analogous to the specification in the previous sub-section.

Similarly, one cannot estimate this model with a double integral, but one can approximate the \(\phi_{it}(h, p)\) with 2-dimensional bins and then employ a semi-parametric technique to estimate \(g(h, p)\). Again the 2 dimensions are progress in the season and the level of the environmental variable. For example, in the case of temperature throughout the growing season, we can define exposure bins over 1°C temperature intervals every week of the growing season. In this example we thus have 1°C bins in the “temperature” dimension, and weekly bins in the “season progress” dimension.

Let me illustrate how to construct the tensor spline necessary to reduce the dimensionality of these 2D bins. Let’s start by considering the basis matrix for a natural cubic spline for the environmental variable, which constitutes the first “dimension”. Let’s denote this matrix \(B_1\). With \(J_1\) degrees of freedom evaluated over \(K_1\) bins, this matrix has a dimension of \(K_1\) rows and \(J_1\) columns. These bins can be 1°C interval if we are dealing with temperature. Similarly, let’s define a basis matrix \(B_2\) for the second “dimension” which is the time or progress within the growing season. With \(J_2\) degrees of freedom evaluated over \(K_2\) bins,
this matrix has a dimension of $K_2$ rows and $J_2$ columns. The associated can be weeks or similarly short time intervals within the growing season.

The tensor basis matrix is constructed based on the kronecker product of these two basis matrices such that $B = B_1 \otimes B_2$ is a matrix with $K_1 K_2$ rows and $J_1 J_2$ columns. Essentially, our 2D bin space has $K_1 K_2$ bins ($K_1$ in the first “variable” dimension and $K_2$ in the second “season progress” dimension) and the goal of this tensor basis matrix is to reduce the dimensionality of this space prior to estimation. This means that our binned data can be stored in a matrix $Z$ with $nT$ and $K_1 K_2$ columns. Each row of that matrix corresponds to one observation (e.g. a county-year $it$). Thus the tensor basis matrix $B$ maps a $nT$ by $K_1 K_2$ matrix $Z$ of 2-dimensional binned data, with columns representing variable and progress bin exposures, into a $nT$ by $J_1 J_2$ matrix $X$ of transformed variables used in the regression analysis. In matrix form, this mapping can be represented as:

$$X_{nT \times J_1 J_2} = Z_{nT \times K_1 K_2} \times B_{K_1 K_2 \times J_1 J_2}$$

One way to visualize how this dimensionality reduction works is to extract one row of $Z$, let’s call it $z_{it}$ with dimension 1 by $K_1 K_2$, and organize it in “two dimensions” in a matrix $z_{it}^{2D}$ of dimension $K_1 \times K_2$. This essentially re-arranges the bins so that we have $K_1$ rows of environmental variable bins, and $K_2$ columns of season progress bins. What the tensor spline is essentially doing is the following transformation:

$$x_{it}^{2D}_{J_1 \times J_2} = B_1^{'}_{J_2 \times K_2} \times z_{it}^{2D}_{K_1 \times K_2} \times B_2_{K_1 \times J_1}$$

where $x_{it}^{2D}$ is the transformed variable for observation $it$ rearranged in two dimensions.

The regression analysis is performed with $J_1 J_2$ regressors, rather than on all the $K_1 K_2$ individual bins. After the estimation, one can recover the marginal effects evaluated at each of the $K_1 K_2$ bins by pre-multiplying the vector $\hat{\Gamma}$ (containing a vector with the $J_1 J_2$ estimated coefficients) by the tensor basis matrix:

$$\hat{\beta}_{1 \times K_1 K_2} = B_{K_1 K_2 \times J_1 J_2} \times \hat{\Gamma}_{J_1 J_2 \times 1}$$

This operation returns a vector $\hat{\beta}$ of temperature effects evaluated at each one of the $K_1 K_2$ original temperature bins in matrix $Z$. To visualize marginal effects on a 2-dimensional space, one would have to rearrange $\hat{\beta}$ in 2 dimensions to obtain a matrix $\hat{\beta}^{2D}$ of dimension $K_2 \times K_1$. This would allow showing marginal effects with season progress bins on the horizontal axis and the variable bins in the vertical axis. One can also easily derive an estimate of the
variance of these temperature effects as follows:

$$Var(\hat{\beta})_{(K_1 K_2) \times (K_1 K_2)} = B_{(K_1 K_2) \times (J_1 J_2)} \times Var(\hat{\Gamma})_{(J_1 J_2) \times (J_1 J_2)} \times B'_{(J_1 J_2) \times (K_1 K_2)}$$

Obtaining standard errors for the marginal effects consists in selecting the squared root of the diagonal elements of $Var(\hat{\beta})$. For more details, I invite the reader to consult the supplementary data in Ortiz-Bobea et al. (2019).

This may seem a bit too theoretical, so the attached code and data provides an implementation for US corn yields (see 3_time-varying_effects.R). In the example, I consider 1°C temperature bins between 0 and 35°C ($K_1 = 36$) and monthly temporal bins between April and October ($K_2 = 7$). Ideally, we would probably want to have finer scale temporal bins (e.g. weeks or pentads) but the use of monthly bins makes this illustration more tractable as it makes use of data already generated for other parts of the chapter. I also select degrees of freedom $J_1 = 6$ and $J_2 = 3$. As a result, our binned matrix $Z$ has $36 \times 7 = 252$ bins. Our tensor basis matrix $B$ has $6 \times 3 = 18$ columns. All these steps are clearly annotated in the R script file.

Figure 11A shows the marginal effects in their 2-dimensional form ($\hat{\beta}^{2D}$). The panel shows that high temperature above 30°C appear detrimental especially in the months between June and August. Marginal effects that are statistically different from zero at a 95% level are highlighted with a star. In contrast, high temperatures appear beneficial early in the season in April, although I later show that result is barely significant.

Figure 11B shows the underlying density over the $36 \times 7 = 252$ bins. As expected, the distribution of temperature in April and and October is toward lower temperature, whereas the distribution is toward higher temperatures in the summer months. This seasonality will naturally affect the precision of estimates for temperature bins that exhibit little to no exposure over certain parts of the year. For instance, there is little exposure above 30°C in the months of April and October. This should render the estimation of marginal effects around that time particularly noisy.

To explore this, Fig. 12 shows a cross-section of marginal effects evaluated at each temporal bin, that is, at each month. The marginal effects in April and October at high levels of temperature are rather noisy and are not significant at a 99% confidence level. Notice there is little to no density (green histogram) at high levels of temperature in those months. In contrast, the marginal effects in July and August are clearly significant at a 99% confidence level and those effects appear more precisely estimated.

This subsection illustrates how one can tractably harness variation in environmental variables within the growing season to estimate within-season time-varying effects.
Notes: Standard errors are clustered at the state and year level. The data covers corn yields over 1981-2020 east of the 100th meridian West. Panel A shows marginal effects of additional exposure to temperature bins in different parts of the growing season. Marginal effects that are statistically different from zero at a 95% level are indicated with a star (*). Panel B shows the density (in days) in each one of the $36 \times 7 = 252$ bins. These bins vertically add to the amount of time in each month. Summing across all months and temperature levels adds up to the total number of days in the growing season (183 days).

Figure 11: Time-varying effects of temperature on US corn yields throughout the growing season.
Notes: Standard errors are clustered at the state level. The data covers corn yields over 1981-2020 east of the 100th meridian West. Precipitation variables were not included. The blue colored bands around the response function corresponds to 95 and 99 percent confidence intervals. The green histogram represents the monthly exposure to all temperature bins.

Figure 12: Time-varying effects of temperature on US corn yields evaluated at each month of the growing season.
This type of model seems particularly useful when researchers seek to harness important within-season differences in crop yield sensitivity. For instance, this might be particularly useful for modeling changes in planting dates or growing seasons, or for estimating high-frequency within-season yield forecasts. Ortiz-Bobea et al. (2019) shows that this approach performs better out of sample than their traditional counterparts that do not allow for time-varying effects (presented in the previous subsection). However, the differences in model fit are not enormous and the magnitude of projected impacts of climate change (without changes in growing seasons) remain similar. One potential reason for this is that very high temperature typically occur in the summer when crops like corn are flowering. This means that the detrimental effect of season-long exposure to extreme temperature in traditional additive models could be primarily reflecting the effect of high temperature (and drought) during the sensitive stages of crop development that happen to coincide with the warmer summer months.

This model also has some limitations. First, the process of constructing bins is somewhat more involved especially if constructing temporal bins finer than a month. However, the code provided with this chapter should alleviate many of these concerns. Another issue is that marginal effects can be fairly imprecise around areas with little to no exposure (see 11B). So perhaps this approach may perform better with standardized variables that exhibit similar distribution across different points of the growing season. That would ensure enough density throughout the entire rectangular support of the 2-dimensional spline.

Potential future research directions may include improvements to this approach including the implementation of penalized B-splines, also know as P-splines, to improve model fit. For instance, the approach implemented in Ortiz-Bobea et al. (2019) to select the flexibility of the tensor spline in both direction was based on a relatively onerous grid search. There are more advanced approaches to implementing these techniques. It might also be possible to explore multi-dimensional splines that allow smooth interactions between environmental indicators throughout the growing season. However, this is likely to require large datasets and possibly experimental data to obtain independent draws of environmental indicators which tend to be highly correlated in observational settings (e.g. high temperature and drought).

For additional reader regarding the use of high-frequency weather data for analyzing climate change impacts I invite the reader to consult Ghanem and Smith (2020). This also relates to a broader literature on model selection (see Cui et al., 2018).
4.5 Spatial dependence

A common characteristic of agricultural data is that neighboring locations exhibit similar values. For instance, a map of crop yields, farm profits or farmland values all appear spatially correlated even at large spatial scales. There are multiple reasons for this. One of them has to do with the spatial dependence of land characteristics such as soil texture, slope or climate. These spatially-dependent factors influence the performance of agriculture which in turns also ends up exhibit spatial dependence. In addition, socio-economic factors can also play a role including local and regional regulations, the presence of irrigation or transportation infrastructure, or the proximity to certain markets or population centers.

In practice, econometric models do not incorporate all these spatially-dependent drivers of our agricultural outcomes of interest. As a result, these omitted variables end up in the error term which ends up also exhibiting spatial dependence. Moreover, weather and climate variables, which are used as predictors, are also spatially dependent. The combination of spatially-dependent error terms and regressors leads particular challenges in regression analysis. For starters, the assumption that errors are independent no longer holds. So adopting standard errors that are simply robust to heteroscedasticity is insufficient. Ignoring positive spatial dependence in the error term in the presence of positively spatially-dependent regressors leads to overconfident inference. Standard errors in those regressions are simply wider than they appear.

The challenge of spatial dependence is analogous to issues that arise in the presence of clustered error terms and regressors \((\text{Cameron and Miller} [2015]; \text{Moulton} [1986, 1990])\). A clustered variable is one that exhibits within-group (cluster) correlation. In observational settings, this correlation is typically positive. Ignoring the positive within-cluster correlation also leads to the estimation of standard errors that are narrower than they truly are.

One common approach to “correct” for spatial dependence is to cluster standard errors at regional scales larger than the unit of analysis. For instance, in a model based on US county data that would be to cluster at the district or state level. What this approach assumes is that there is a common “shock” to all locations within that cluster but no correlation between locations across cluster boundaries. In the case of US counties, that would mean that neighboring counties exhibit correlated errors or regressors within states, but that there is no correlation across state lines. Given that the drivers of many agricultural outcomes are natural in nature and do not follow administrative borders, this assumption is unlikely to be valid, at least \(a\ priori\).

A more conceptually appropriate way to correct for spatial dependence in a linear model is to correct directly for spatial dependence. This would allow to account for smoother patterns of correlation between neighboring locations irrespective of whether locations fall
within the same state or district. One approach to achieve this is the adopting a spatial heteroscedasticity and autocorrelation consistent (HAC) estimator of the variance covariance matrix introduced in Conley (1999). The idea is close to a spatial analogue to the heteroscedasticity and autocorrelation consistent estimator of the covariance matrix introduced in Newey and West (1986) to address serial correlation. The key idea behind the spatial HAC estimator is the use of a kernel that weighs the cross-products in the computation of the covariance matrix based on the spatial distance between observations. The implementation requires a distance threshold (say 500 miles) beyond which one assumes there is no correlation between observations. This is typically implemented via a Bartlett window which assigns the value of 1 for the observation at hand (distance equal 0) and decreases linearly down to 0 when one reaches the threshold. Beyond that point the assigned weight is 0.

The R code that accompanies this chapter provides an implementation of the spatial HAC standard errors (see 4_spatial_dependence.R). The implementation allows the specification of multiple distance thresholds as well as that of various weighting kernels in addition to the more common Bartlett window.

Another approach to account for spatial dependence is to harness the spatial dependence in the estimation to obtain a more efficient estimator. This can be achieved with a Spatial Error Model (SEM) which can be estimated via GMM or MLE (Anselin, 1988). This approach is relatively uncommon and can be found in a few studies in the literature (e.g. Schlenker et al., 2006). The difference between the spatial HAC correction above and the SEM is analogous to the difference between correcting for heteroscedasticity and estimating a Generalized or Weighted Least Squares. In the former case one seeks to correct the estimation of standard errors of an otherwise inefficient estimator, whereas in the latter one tries to harness more information about the distribution of the error term to derive a more efficient estimator.

One perceived disadvantage of the SEM is that it requires specifying a weight matrix, imposing some structure on the nature of the spatial dependence between neighboring observations. However, these concerns are likely overblown (LeSage and Pace, 2014). Moreover, doesn’t the imposition of a kernel and a cutoff distance in the estimation of the spatial HAC estimator also impose some form of structure to the nature of spatial dependence? One approach to avoid unnecessary criticism by reviewers unfamiliar with the SEM is to present the SEM results along with results based on OLS (corrected for spatial dependence). Note however, that the SEM and OLS estimates are consistent in the absence of an omitted variable, but the presence of an omitted variable induces different types of biases in these two estimators. This situation permits the implementation of a spatial Hausman test (Pace and LeSage, 2008). The R code that accompanies this chapter provides an implementation of
the SEM model for balanced panel models. The implementation allows the specification of various types of weight matrices.

I illustrate the marginal effects of exposure to various temperature levels with various standard errors for OLS and for the SEM in Fig. 13. Panels A through F are based on OLS and have the same point estimates. Panel G is based on the SEM, which is a different estimator, so the response function is different.

Panel A of Fig. 13 shows a confidence band that assumes errors are independent and identically distributed. Even beforehand, we know this assumption is incorrect because the error is spatially dependent so these confidence band is deceptively narrow. The R code shows that the residuals appear highly correlated and that a Moran’s I test rejects the hypothesis of no spatial correlation. Note that correcting simply for heteroscedasticity in B does not change things much.

Interestingly, Fig. 13C and D show that clustering the standard error by state or by state and year leads to much more conservative standard errors which leads to a much wider confidence band around our response function. While many of the effects of temperature exposure in the 0-25°C largely indistinguishable from zero at conventional levels, the effects of exposure beyond 30°C appear clearly detrimental.

Figure 13E is based on the spatial HAC standard errors proposed in Conley (1999) using a cutoff distance of 500 miles. Panel F shows the confidence band when the cutoff is increased to 1000 miles. Note these standard errors are of a similar magnitude to those clustered by state or by state and year. This is an interesting finding because it suggested that in some cases, clustering may yield similarly conservative estimates despite not accounting for cross-cluster correlations.

Finally, Fig. 13G shows estimates based on the SEM estimated via Maximum Likelihood. Note that the implementation in R only allows balanced panels. So while the OLS models where estimated with an unbalanced panel of 2,248 counties over 1981-2020 and 69,190 observations, the SEM was estimated with a balanced panel of 599 counties over the same period with only 23,960 observations. And yet, the standard errors —which are conceptually correct— are much narrower. As explained above, this estimator is more efficient than OLS because it harnesses information about spatial dependence in the estimation.

4.6 Common robustness and sensitivity checks

It is often common for reviewers in the peer review process to ask authors to perform additional robustness or sensitivity checks. While these requests can often feel like an unnecessary burden to authors, these checks can help build more confidence on the results and clarify
Notes: The data covers corn yields over 1981-2020 east of the 100th meridian West. Precipitation variables were included in the regression but coefficients are not shown. The blue colored bands around the response function corresponds to 95 and 99 percent confidence intervals for each type of standard error. The green histogram represents the growing-season of exposure to all temperature bins. The response function is based on a natural cubic spline with 7 degrees of freedom and 1°C bins between 0 and 38°C over the April-September growing season. Note the Spatial Error Model (SEM) is estimated based on a smaller balanced panel.

Figure 13: Different standard errors and estimators for the effects of temperature exposure on corn yields.
to what degree certain modeling assumptions have an outsized influence. This relates to a large degree to the classic call in Leamer (1983) for the systematic adoption of sensitivity checks in empirical research.

Perhaps the most basic type of check is about heterogeneity, which can generally be manifested either in space or time. When estimating weather effects on economic outcomes in a panel setting, it is generally a good idea to test whether coefficients are stable across major regional or temporal subsets of the data (e.g. with a Wald test). Understanding heterogeneity is critical and can even become the primary focus of a study. For instance, Butler and Huybers (2013) find that corn yields in hotter regions in the US appear less sensitive to extreme heat relative to colder regions, which the authors suggest is indicative of adaptation to climate change (see Schlenker et al., 2013 for a response). Analogously, Ortiz-Bobea et al. (2018) explores temporal heterogeneity in the response function of US agricultural TFP to document the rising sensitivity of Midwestern agriculture to higher temperature.

Another aspect that often receives considerable scrutiny in empirical work are nonlinearities in how weather or climate variables affect agricultural outcomes of interest. For instance, Mendelsohn et al. (1994) included linear and quadratic coefficients for monthly temperature and precipitation variables in the specification. This captures the idea that while certain weather conditions are optimal for agricultural production, extreme weather tends to be detrimental. The work of Schlenker and Roberts (2009a) also highlighted the importance of nonlinearities for temperature by introducing a semi-parametric approach that flexibly harnesses the influence of daily temperature exposure on crop yields.

Sometimes, however, regression coefficients are difficult to interpret directly, particularly when dealing with higher term polynomials or splines. As a result, a useful approach is to compare the impact of a uniform warming (e.g. +2°C) or a percentage change in precipitation across alternative specifications. There is a broad recognition that temperature effects may not only capture heat stress but also moisture stress (see Lobell et al., 2013 or Ortiz-Bobea et al., 2019) so the emphasis tends to be justifiably more focused on projected impacts than on the values of the estimated parameters themselves. This is perhaps slightly different from other research areas where the value of estimated parameters are quantities with a clear theoretical grounding in economics (e.g. a price elasticity). In general, it is advisable to compare models, not only in terms of their fit (ideally out of sample) but also in terms of the associated impacts of some specific change in the distribution of weather or climatic conditions. This facilitates comparison across models.

Another modeling choice that receives some scrutiny is the choice of the weather dataset and how it is aggregated in space or time. It is not uncommon to see researchers reporting
results based on alternative weather datasets, or alternative ways of spatially aggregating weather to the unit of analysis. As indicated earlier in this chapter, one can spatially aggregate gridded weather data based on a variety of different of weighting schemes (e.g. cropland or cropland and pasture weights, etc). The same goes for spatially interpolated weather station data. The choice of seasons and how weather conditions are aggregated over time, is also a common point of scrutiny. In general, it is difficult to know a priori the role of these modeling assumptions in our results. It is thus generally the case that researchers present results based on alternative definitions of the growing season.

An important aspect of conducting empirical research is appropriately characterizing the uncertainty around estimated parameters. The assumption that errors are independent and identically distributed is virtually always violated in observational settings. When analyzing climate-economy linkages, weather conditions tend to be strongly spatially correlated across great distances (see previous subsection). And just like economic outcomes, their unobservable drivers are also spatially dependent. Ignoring this positive spatial dependence typically leads to overconfidence by underestimating standard errors. In such cases, a common solution is to correct for spatial dependence in a linear model using spatial HAC standard errors (e.g. Conley [1999]). It is also common to see researchers cluster standard errors at relatively large regional levels (e.g. at the state level in a county-level panel setting) in order to capture the contemporaneous dependence. However, such clustering approaches would not account for correlation across clusters that may be occurring. But as shown in the previous subsection, these approaches can point to similar standard errors.

It is also not uncommon to see the adoption of weighted regressions, where observations are weighted based on some metric indicative of each observation’s variance, like acreage. The idea is that the variance of observations in locations with small acreage is higher, so these would be given a smaller weight in a weighted least squares estimation. However, this approach poses some challenges regarding the interpretation of the results if the introduction of regression weight drastically alter the estimated coefficients. This may signal a misspecification or an unaccounted heterogeneity (see Solon et al. [2015] for guidance on regression weights). The adoption of spatial HAC errors seems more appropriate, at least conceptually, because it jointly accounts for heteroscedasticity and spatial dependence.

An increasingly common exercise in empirical studies is the implementation of “placebo” checks or tests (Eggers et al. [2021]). The idea behind a placebo check is that a treatment should not appear to have an effect on an untreated unit of analysis. In our context, for instance, it means that a weather shock in location $i$ at time $t$ should have no effect on the outcome of interest in a different location or time period. This is a bit tricky because weather is not independently “assigned”, meaning that similar weather shocks occur in neigh-
boring locations, so a weather shock in one location may well appear to have an effect in neighboring locations simply because of such contemporaneous correlations. We could also make an analogous point in the time dimension in the presence of serially correlated weather conditions (e.g. in places where droughts tend to be multi-year phenomena).

A common placebo check in panel settings is to estimate the model with lead weather. It is reasonable to assume that future weather fluctuations, which are arguably impossible to predict accurately in advance, should have no bearing on a current outcome. An analogous spatial version of this check is to simply randomly reassign weather of other locations to the outcome variable. In a large enough panel, this “reshuffling” should result in results that are, on average, insignificantly different from zero. However, note that it is still possible to get a significant effect by chance. This is a key weakness of such simple placebo checks, which are not actual statistical tests.

A preferable approach is to conduct a placebo test in the form of a permutation test (also called randomization test). These are non-parametric tests for which the researcher constructs the distribution of a test statistic under the null hypothesis of “no effect”. In a setting estimating the effect of weather on an economic outcome, the idea is to reshuffle the weather data across units, re-estimate the model with the permuted weather predictors, store the coefficients and repeat this process, say, ten thousand times. The resulting distribution of this spurious coefficients should be centered around zero. The researcher can then contrast the sample estimate, i.e. the estimate with the correctly matched data, to this distribution to obtain a p-value. This procedure seems straightforward when assessing a single coefficient, but the analysis can be done when estimating a quadratic relationship (e.g. see Figure 2 in [Ortiz-Bobea et al.] 2021). Another approach that might help conducting multiple simultaneous tests is to derive the distribution of the test statistic as the linear combination of coefficients (e.g. computing the impact of a 2°C warming at each iteration).

This section highlights that conducting empirical research in this area requires making a relatively large number of modeling assumptions along the way. In order to build confidence in our results, it is critical to justify these assumptions and, ideally, to show to what extend results are sensitive to these. However, presenting the results of the paper under many alternative sets of modeling assumptions can be tedious and make any paper feel overburdened. For instance, the online appendix in [Ortiz-Bobea et al.] (2019) is 74 pages long and includes 6 pages of single-spaced text, 57 supplementary figures and 7 tables.

One strategy to show robustness checks in a more parsimonious way is to present the main estimate in a study under alternative modeling assumptions in a specification chart or curve [Simonsohn et al.] 2019. This type of chart can summarize a large number of estimates in a single visualization, which helps authors and readers better understand the
Notes: Standard errors are clustered at the state level. The data covers corn yields over 1981-2020 east of the 100th meridian West. The models are sorted by adjusted R2 with the best-fitting model shown on the right.

Figure 14: Estimated impact of a 2°C for 72 alternative specifications.
important of specific modeling assumptions. Rather than thinking about these charts as a way to show “robustness”, it is preferable to think about this as an exercise in transparency and as a way to characterize the potential uncertainty regarding model selection.

The R code provided with this chapters provides an implementation of a specification chart with a reproducible example (see 5_robustness_checks.R). In this example I estimate a statistical crop yield model based on a panel of corn yields east of the 100th meridian West over the 1981-2020 period. The dependent variable is log yield and I consider a wide range of variation of the model specification. Specifically, I explore the role of the temperature variable (Tmax, Tmean or Tmin), the inclusion of a precipitation variable, the adoption of a quadratic or cubic functional form for the weather regressors, the definition of the growing season (March-August, April-September or the entire year) and whether a quadratic time trend in the regression model is estimated by state or pooled for all counties. Obviously, we could add more checks.

It is very common for researchers to conduct analysis and show results based on a particular “baseline” model. Let’s say that our baseline model is based on Tmean, includes precipitation, adopts a quadratic response function, adopts a growing season defined over March-August, and includes a common time trend for the sample. One way to show how this model compares to alternative models is to conduct the analysis on an exhaustive combination of these modeling assumptions. However, comparing coefficients across models with different temperature variables and functional forms can be intractable. A better approach is to compare the implied effect of a, say, 2°C warming.

Figure 14 shows the effect of a 2°C warming for 72 different specifications. In this example, I have sorted the models from the lowest to the highest fitting specification based on the adjusted R2. Models could also be sorted based on any other criteria including out-of-sample Means Squared Error, their point estimate or simply preserve the original order in which the models were stored in the input table. What is interesting here is that the best fitting models (on the right) tend to point to larger negative impacts. The baseline model we selected, highlighted in red, is not much different than many other well-fitting models.

A few things stand out while exploring this specification chart. First, models based on Tmin tend to point to small impacts and perform relatively poorly in terms of fit. Second, models based on Tmax tend to point to larger impacts and fit better, especially when coupled with precipitation variables. Third, there is no discernible difference between models estimated with a quadratic or a cubic functional form. Fourth, the shorter March-August season tends to fit better whereas the full annual season performs more poorly. Finally, models estimated based on a state-level time trend tend to perform better in terms of fit, and also put to larger impacts relative to models with pooled time trends.
This exercise shows that modeling assumption can drastically alter reported estimates. Being upfront and transparent about how the main baseline results shown in the paper can change with modeling assumptions should build confidence in the reader that results were not cherry picked. Figure 14 is fully reproducible with the included R code. The code also includes a function that allows the creation of such charts with relative ease. I have also included a reproducible example in spec_chart_reproducible_example.R that showcases all the capabilities of this function.

5 Conclusion

This chapter provides an overview of the economic literature analyzing climate change impacts and adaptation in agriculture. The first subsection cover some basic concepts and knowledge necessary to understand the discussions and debate in the literature. This includes overviews of common sources and the nature of weather and climate change data.

The following subsection cover a range of topics with an emphasis on methods for analyzing various aspects of the impacts of climate change on agriculture. I discuss early studies based on biophysical approaches and their evolution and subsequent integration with trade models. I then describe the emergence and motivation behind econometric techniques and the explosion of empirical studies analyzing impacts of weather fluctuations on agricultural outcomes based on longitudinal data. I also discuss emerging efforts to link statistical and biophysical techniques, as well as new methods to combine the advantages of cross-sectional and longitudinal methods in the empirical literature. I also spend some time discussing work exploring various mechanism of adaptation, including irrigation, crop choices, planting and cropping frequency decisions. I finally provide a very short overview of recent work analyzing the role of trade in determining climate change impacts. I conclude with some possible future directions of research and collaborations with non-economists.

The last subsection is a unique effort to provide a hands on introduction to new researchers in this literature. The subsection discusses very practical empirical challenges as well as common tasks necessary to estimate more sophisticated empirical models in the field. That part also discusses the estimation of standard errors in the presence of spatial dependence. I also spend a bit of time discussing common sensitivity checks in the literature and introduce a parsimonious way of presenting numerous robustness checks without overwhelming the reader.

All of the figures in this chapter are fully reproducible. This code represents the entire workflow including downloading some of the weather datasets, transforming the weather data, spatially aggregating and interpolating weather data, estimating various types of semi-
parametric models and the construction of various types of standard errors that are relevant in this literature. It is my hope that this chapter removes some of the barriers to entry to this field of research. Thank you for reading.

References

Adams, Richard M., “Global Climate Change and Agriculture: An Economic Perspective,” American Journal of Agricultural Economics, 1989, 71 (5).

_ , Cynthia Rosenzweig, Robert M. Peart, Joe T. Ritchie, Bruce A. McCarl, J. David Gloyer, R. Bruce Curry, James W. Jones, Kenneth J. Boote, and L. Hartwell Allen, “Global climate change and US agriculture,” Nature, May 1990, 345 (6272), 219–224.

_ , Ronald A. Fleming, Ching-Chang Chang, Bruce A. McCarl, and Cynthia Rosenzweig, “A reassessment of the economic effects of global climate change on U.S. agriculture,” Climatic Change, June 1995, 30 (2), 147–167.

Angrist, Joshua and Jörn-Steffen Pischke, “The Credibility Revolution in Empirical Economics: How Better Research Design is Taking the Con out of Econometrics,” Working Paper 15794, National Bureau of Economic Research March 2010.

Annan, Francis and Wolfram Schlenker, “Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat,” The American Economic Review, May 2015, 105 (5), 262–266.

Anselin, Luc, Spatial Econometrics: Methods and Models, Vol. 4 of Studies in Operational Regional Science, Dordrecht: Springer Netherlands, 1988.

Antle, John M., “Sequential Decision Making in Production Models,” American Journal of Agricultural Economics, May 1983, 65 (2), 282–290. ArticleType: primary_article / Full publication date: May, 1983 / Copyright © 1983 Agricultural & Applied Economics Association.

_ and Claudio O. Stöckle, “Climate Impacts on Agriculture: Insights from Agronomic-Economic Analysis,” Review of Environmental Economics and Policy, July 2017, 11 (2), 299–318. Publisher: The University of Chicago Press.

Arellano-Gonzalez, Jesus and Frances C. Moore, “Intertemporal Arbitrage of Water and Long-Term Agricultural Investments: Drought, Groundwater Banking, and Perennial
Cropping Decisions in California,” *American Journal of Agricultural Economics*, 2020, 102 (5), 1368–1382. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ajae.12123.

**Ashenfelter, Orley and Karl Storchmann**, “Using Hedonic Models of Solar Radiation and Weather to Assess the Economic Effect of Climate Change: The Case of Mosel Valley Vineyards,” _The Review of Economics and Statistics_, February 2010, 92 (2), 333–349. Publisher: MIT Press.

_ and _, “The Economics of Wine, Weather, and Climate Change,” _Review of Environmental Economics and Policy_, January 2016, 10 (1), 25–46. Publisher: The University of Chicago Press.

Asseng, Senthold, Pierre Martre, Andrea Maiorano, Reimund P. Rötter, Garry J. O’Leary, Glenn J. Fitzgerald, Christine Girousse, Rosella Motzo, Francesco Giunta, M. Ali Babar, Matthew P. Reynolds, Ahmed M. S. Kheir, Peter J. Thorburn, Katharina Waha, Alex C. Ruane, Pramod K. Aggarwal, Mukhtar Ahmed, Juraj Balkovič, Bruno Basso, Christian Biernath, Marco Bindi, Davide Cammarano, Andrew J. Challinor, Giacomo De Sanctis, Benjamin Dumont, Ehsan Eyshi Rezaei, Elias Fereres, Roberto Ferrise, Margarita Garcia-Vila, Sebastian Gayler, Yujing Gao, Heidi Horan, Gerrit Hoogenboom, R. César Izaurralde, Mohamed Jabloun, Curtis D. Jones, Belay T. Kassie, Kurt-Christian Kersebaum, Christian Klein, Ann-Kristin Koehler, Bing Liu, Sara Minoli, Manuel Montesino San Martin, Christoph Müller, Soora Naresh Kumar, Claas Nendel, Jørgen Eivind Olesen, Taru Palosuo, John R. Porter, Eckart Priesack, Dominique Ripoche, Mikhail A. Semenov, Claudio Stöckle, Pierre Stratonovitch, Thilo Streck, Iwan Supit, Fulu Tao, Marijn Van der Velde, Daniel Wallach, Enli Wang, Heidi Webber, Joost Wolf, Liujuin Xiao, Zhao Zhang, Zhigan Zhao, Yan Zhu, and Frank Ewert, “Climate change impact and adaptation for wheat protein,” *Global Change Biology*, 2019, 25 (1), 155–173. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/gcb.14481.

**Auffhammer, Maximilian, Solomon M. Hsiang, Wolfram Schlenker, and Adam Sobel**, “Using weather data and climate model output in economic analyses of climate change,” _Review of Environmental Economics and Policy_, 2013, p. ret016.

**Baldos, Uris Lantz C. and Thomas W. Hertel**, “Global food security in 2050: the role of agricultural productivity and climate change,” *Australian Journal of Agricultural and Resource Economics*, 2014, 58 (4), 554–570. Publisher: Wiley Online Library.
Black, J. Roy and Stanley R. Thompson, “Some Evidence on Weather-Crop-Yield Interaction,” *American Journal of Agricultural Economics*, 1978, 60 (3), 540–543.

Blanc, Elodie and Wolfram Schlenker, “The Use of Panel Models in Assessments of Climate Impacts on Agriculture,” *Review of Environmental Economics and Policy*, July 2017, 11 (2), 258–279. Publisher: The University of Chicago Press.

Bonhomme, Raymond, “Bases and limits to using ‘[degree.day’ units,” *European Journal of Agronomy*, July 2000, 13 (1), 1–10.

Branco, Danyelle and José Feres, “Weather Shocks and Labor Allocation: Evidence from Rural Brazil,” *American Journal of Agricultural Economics*, 2020, n/a (n/a). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ajae.12171.

Buck, Steven, Maximilian Auffhammer, and David Sunding, “Land Markets and the Value of Water: Hedonic Analysis Using Repeat Sales of Farmland,” *American Journal of Agricultural Economics*, 2014, 96 (4), 953–969. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1093/ajae/aau013.

Burke, Marshall and Kyle Emerick, “Adaptation to Climate Change: Evidence from US Agriculture,” *American Economic Journal: Economic Policy*, August 2016, 8 (3), 106–140.

Butler, Ethan E. and Peter Huybers, “Adaptation of US maize to temperature variations,” *Nature Climate Change*, January 2013, 3 (1), 68–72.

Cameron, A. Colin and Douglas L. Miller, “A Practitioner’s Guide to Cluster-Robust Inference,” *Journal of Human Resources*, March 2015, 50 (2), 317–372. Publisher: University of Wisconsin Press.

Carter, Colin, Xiaomeng Cui, Dalia Ghanem, and Pierre Mérel, “Identifying the Economic Impacts of Climate Change on Agriculture,” *Annual Review of Resource Economics*, 2018, 10 (1), 361–380. _eprint: https://doi.org/10.1146/annurev-resource-100517-022938.

Challinor, Andrew J., Ben Parkes, and Julian Ramirez-Villegas, “Crop yield response to climate change varies with cropping intensity,” *Global Change Biology*, 2015, 21 (4), 1679–1688. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/gcb.12808.

Christian, Paul, Florence Kondylis, Valerie Mueller, Astrid Zwager, and Tobias Siegfried, “Monitoring Water for Conservation: A Proof of Concept from
Mozambique,” *American Journal of Agricultural Economics*, 2021, n/a (n/a). _eprint:_ https://onlinelibrary.wiley.com/doi/pdf/10.1111/ajae.12209.

Cline, William R., “The Impact of Global Warming of Agriculture: Comment,” *The American Economic Review*, December 1996, 86 (5), 1309–1311.

Cohn, Avery S., Leah K. VanWey, Stephanie A. Spera, and John F. Mustard, “Cropping frequency and area response to climate variability can exceed yield response,” *Nature Climate Change*, June 2016, 6 (6), 601–604. Number: 6 Publisher: Nature Publishing Group.

Conley, T. G., “GMM estimation with cross sectional dependence,” *Journal of Econometrics*, September 1999, 92 (1), 1–45.

Costinot, Arnaud, Dave Donaldson, and Cory Smith, “Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world,” *Journal of Political Economy*, 2016, 124 (1), 205–248. Publisher: University of Chicago Press Chicago, IL.

Cui, Xiaomeng, “Beyond Yield Response: Weather Shocks and Crop Abandonment,” *Journal of the Association of Environmental and Resource Economists*, May 2020, 7 (5), 901–932. Publisher: The University of Chicago Press.

_ , Dalia Ghanem, and Todd Kuffner, “On model selection criteria for climate change impact studies,” August 2018.

Dalhaus, Tobias, Wolfram Schlenker, Michael M. Blanke, Esther Bravin, and Robert Finger, “The Effects of Extreme Weather on Apple Quality,” *Scientific Reports*, May 2020, 10 (1), 7919. Number: 1 Publisher: Nature Publishing Group.

Daly, Christopher, G. H. Taylor, and W. P. Gibson, “The PRISM approach to mapping precipitation and temperature,” in “Proc., 10th AMS Conf. on Applied Climatology” Citeseer 1997, pp. 20–23.

Darwin, Roy, “The Impact of Global Warming on Agriculture: A Ricardian Analysis: Comment,” *The American Economic Review*, September 1999, 89 (4), 1049–1052.

Decker, Wayne L., “Developments in agricultural meteorology as a guide to its potential for the twenty-first century,” *Agricultural and Forest Meteorology*, June 1994, 69 (1), 9–25.
Deschênes, Olivier and Michael Greenstone, “Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US,” National Bureau of Economic Research Working Paper Series, June 2007, No. 13178.

and , “The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Reply,” American Economic Review, December 2012, 102 (7), 3761–3773.

Druckenmiller, Hannah and Solomon Hsiang, “Accounting for Unobservable Heterogeneity in Cross Section Using Spatial First Differences,” Working Paper 25177, National Bureau of Economic Research October 2018. Series: Working Paper Series.

Easterling, William E., Mary S. McKenney, Norman J. Rosenberg, and Kathleen M. Lemon, “Simulations of crop response to climate change: effects with present technology and no adjustments (the ‘dumb farmer’ scenario),” Agricultural and Forest Meteorology, April 1992, 59 (1-2), 53–73.

Edwards, Eric C. and Steven M. Smith, “The Role of Irrigation in the Development of Agriculture in the United States,” The Journal of Economic History, December 2018, 78 (4), 1103–1141. Num Pages: 1103-1141 Place: Santa Clara, United Kingdom Publisher: Cambridge University Press Section: Article.

Eggers, Andrew C., Guadalupe Tuñón, and Allan Dafoe, “Placebo Tests for Causal Inference,” 2021.

Elhorst, J. Paul, “Applied Spatial Econometrics: Raising the Bar,” Spatial Economic Analysis, March 2010, 5 (1), 9–28.

Elliott, Joshua, Delphine Deryng, Christoph Müller, Katja Frieler, Markus Konzmann, Dieter Gerten, Michael Glotter, Martina Flörke, Yoshihide Wada, Neil Best, Stephanie Eisner, Balázs M. Fekete, Christian Folberth, Ian Foster, Simon N. Gosling, Ingjerd Haddeland, Nikolay Khabarov, Fulco Ludwig, Yoshimitsu Masaki, Stefan Olin, Cynthia Rosenzweig, Alex C. Ruane, Yusuke Satoh, Erwin Schmid, Tobias Stacke, Qiu Hong Tang, and Dominik Wisser, “Constraints and potentials of future irrigation water availability on agricultural production under climate change,” Proceedings of the National Academy of Sciences, March 2014, 111 (9), 3239–3244. Publisher: National Academy of Sciences Section: Physical Sciences.

Erda, Lin, Xiong Wei, Ju Hui, Xu Yinlong, Li Yue, Bai Liping, and Xie Liyong, “Climate change impacts on crop yield and quality with CO2 fertilization in China,”
Fageria, N. K., V. C. Baligar, and R. B. Clark, *Physiology of crop production*, Routledge, May 2006.

Fezzi, Carlo and Ian Bateman, “The Impact of Climate Change on Agriculture: Non-linear Effects and Aggregation Bias in Ricardian Models of Farmland Values,” *Journal of the Association of Environmental and Resource Economists*, March 2015, 2 (1), 57–92.

Finkelshtain, Israel, Iddo Kan, and Mickey Rapaport-Rom, “Substitutability of Freshwater and Non-Freshwater Sources in Irrigation: an Econometric Analysis,” *American Journal of Agricultural Economics*, 2020, 102 (4), 1105–1134. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/ajae.12043.

Fischer, Günther, Francesco N. Tubiello, Harrij van Velthuizen, and David A. Wiberg, “Climate change impacts on irrigation water requirements: Effects of mitigation, 1990–2080,” *Technological Forecasting and Social Change*, September 2007, 74 (7), 1083–1107.

Fisher, A., M. Hanemann, M. Roberts, and W. Schlenker, “The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather: comment,” *American Economic Review*, 2012, 102 (7), 3749–3760.

Gammans, Matthew, Pierre Mérel, and Ariel Ortiz-Bobea, “Negative impacts of climate change on cereal yields: statistical evidence from France,” *Environmental Research Letters*, 2017, 12 (5), 054007.

Garg, Teevrat, Maulik Jagnani, and Vis Taraz, “Temperature and Human Capital in India,” *Journal of the Association of Environmental and Resource Economists*, May 2020, 7 (6), 1113–1150. Publisher: The University of Chicago Press.
Gatti, Nicolas, Kathy Baylis, and Benjamin Crost, “Can Irrigation Infrastructure Mitigate the Effect of Rainfall Shocks on Conflict? Evidence from Indonesia,” *American Journal of Agricultural Economics*, 2021, 103 (1), 211–231. _eprint:_ https://onlinelibrary.wiley.com/doi/pdf/10.1002/ajae.12092.

Ghanem, Dalia and Aaron Smith, “What Are the Benefits of High-Frequency Data for Fixed Effects Panel Models?,” *Journal of the Association of Environmental and Resource Economists*, August 2020, 8 (2), 199–234. Publisher: The University of Chicago Press.

Gouel, Christophe and David Laborde, “The crucial role of domestic and international market-mediated adaptation to climate change,” *Journal of Environmental Economics and Management*, March 2021, 106, 102408.

Griliches, Zvi and Jerry A. Hausman, “Errors in variables in panel data,” *Journal of Econometrics*, 1986, 31 (1), 93–118.

Gupta, Anil K., “Origin of agriculture and domestication of plants and animals linked to early Holocene climate amelioration,” *Current Science*, 2004, 87 (1), 54–59. Publisher: Temporary Publisher.

Hagerty, Nick, “Adaptation to Water Scarcity in Irrigated Agriculture in California,” in “AGU Fall Meeting 2020” AGU 2020.

Hamza, M. A. and W. K. Anderson, “Soil compaction in cropping systems: A review of the nature, causes and possible solutions,” *Soil and Tillage Research*, June 2005, 82 (2), 121–145.

Heim, Richard R., “A Review of Twentieth-Century Drought Indices Used in the United States,” *Bulletin of the American Meteorological Society*, August 2002, 83 (8), 1149–1166. Publisher: American Meteorological Society Section: Bulletin of the American Meteorological Society.

Hendricks, Nathan P., “Potential Benefits from Innovations to Reduce Heat and Water Stress in Agriculture,” *Journal of the Association of Environmental and Resource Economists*, February 2018, 5 (3), 545–576.

Hertel, Thomas, “Chapter 12 - Global Applied General Equilibrium Analysis Using the Global Trade Analysis Project Framework,” in Peter B. Dixon and Dale W. Jorgenson, eds., *Handbook of Computable General Equilibrium Modeling*, Vol. 1 of *Handbook of Computable General Equilibrium Modeling SET, Vols. 1A and 1B*, Elsevier, January 2013, pp. 815–876.
Hertel, Thomas W., Marshall B. Burke, and David B. Lobell, “The poverty implications of climate-induced crop yield changes by 2030,” *Global Environmental Change*, October 2010, 20 (4), 577–585.

Hodges, J. A., “The Effect of Rainfall and Temperature on Corn Yields in Kansas,” *Journal of Farm Economics*, April 1931, 13 (2), 305–318.

Hornbeck, Richard, “The Enduring Impact of the American Dust Bowl: Short- and Long-Run Adjustments to Environmental Catastrophe,” *American Economic Review*, June 2012, 102 (4), 1477–1507.

_ and Pinar Keskin, “The historically evolving impact of the ogallala aquifer: Agricultural adaptation to groundwater and drought,” *American Economic Journal: Applied Economics*, 2014, 6 (1), 190–219.

Hsiang, Solomon, David Lobell, Michael Roberts, and Wolfram Schlenker, “Climate and Crop Yields in Australia, Brazil, China, Europe and the United States,” SSRN Scholarly Paper ID 2977571, Social Science Research Network, Rochester, NY January 2013.

Hudson, I. L and M. R. Keatley, *Phenological research: methods for environmental and climate change analysis*, Springer Verlag, 2009.

Iizumi, Toshichika and Navin Ramankutty, “How do weather and climate influence cropping area and intensity?,” *Global Food Security*, March 2015, 4, 46–50.

IPCC, “Climate change 2014 impacts, adaptation, and vulnerability,” 2014.

Janssens, Charlotte, Petr Havlík, Tamás Krisztin, Justin Baker, Stefan Frank, Tomoko Hasegawa, David Leclère, Sara Ohrel, Shaun Ragnauth, Erwin Schmid, Hugo Valin, Nicole Van Lipzig, and Miet Maertens, “Global hunger and climate change adaptation through international trade,” *Nature Climate Change*, September 2020, 10 (9), 829–835. Number: 9 Publisher: Nature Publishing Group.

Kahn, Matthew E, “Climate Change Adaptation: Lessons from Urban Economics,” Working Paper 20716, National Bureau of Economic Research November 2014. Series: Working Paper Series.

Kaiser, Harry M., Susan J. Riha, Daniel S. Wilks, David G. Rossiter, and Radha Sampath, “A Farm-Level Analysis of Economic and Agronomic Impacts of Gradual Climatic Warming,” *American Journal of Agricultural Economics*, May 1993, 75 (2), 387–398.
Kaufmann, Robert K., “The impact of climate change on US agriculture: a response to Mendelssohn et al. (1994),” *Ecological Economics*, August 1998, 26 (2), 113–119.

_ and Seth E. Snell_, “A Biophysical Model of Corn Yield: Integrating Climatic and Social Determinants,” *American Journal of Agricultural Economics*, February 1997, 79 (1), 178–190.

Kawasaki, Kentaro and Shinsuke Uchida, “Quality Matters More Than Quantity: Asymmetric Temperature Effects on Crop Yield and Quality Grade,” *American Journal of Agricultural Economics*, 2016, 98 (4), 1195–1209. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1093/ajae/aaw036.

Kolstad, Charles D. and Frances C. Moore, “Estimating the Economic Impacts of Climate Change Using Weather Observations,” *Review of Environmental Economics and Policy*, January 2020, 14 (1), 1–24. Publisher: The University of Chicago Press.

Kucharik, Christopher J., “A Multidecadal Trend of Earlier Corn Planting in the Central USA,” *Agronomy Journal*, 2006, 98 (6), 1544.

_ , “Contribution of Planting Date Trends to Increased Maize Yields in the Central United States,”* Agronomy Journal*, 2008, 100 (2), 328.

Leamer, Edward E., “Let’s Take the Con Out of Econometrics,” *The American Economic Review*, March 1983, 73 (1), 31–43.

Leiserowitz, Anthony, Edward W. Maibach, Connie Roser-Renouf, Geoff Feinberg, and Peter Howe, “Climate change in the American mind: Americans’ global warming beliefs and attitudes in April 2013,” *Available at SSRN 2298705*, 2013.

LeSage, James P. and R. Kelley Pace, *Introduction to Spatial Econometrics*, Chapman and Hall/CRC, January 2009.

_ and _ , “The Biggest Myth in Spatial,” *Econometrics*, December 2014, 2 (4), 217–249.

Lesk, Corey, Pedram Rowhani, and Navin Ramankutty, “Influence of extreme weather disasters on global crop production,” *Nature*, January 2016, 529 (7584), 84–87.

Liang, Xin-Zhong, You Wu, Robert G. Chambers, Daniel L. Schmoldt, Wei Gao, Chaoshun Liu, Yan-An Liu, Chao Sun, and Jennifer A. Kennedy, “Determining climate effects on US total agricultural productivity,” *Proceedings of the National Academy of Sciences*, 2017, 114 (12), E2285–E2292. Publisher: National Acad Sciences.
Liu, Bing, Senthold Asseng, Christoph Müller, Frank Ewert, Joshua Elliott, David B. Lobell, Pierre Martre, Alex C. Ruane, Daniel Wallach, James W. Jones, Cynthia Rosenzweig, Pramod K. Aggarwal, Phillip D. Alderman, Jakarat Anothai, Bruno Basso, Christian Biernath, Davide Cammarano, Andy Challinor, Delphine Deryng, Giacomo De Sanctis, Jordi Doltra, Elias Fereres, Christian Folberth, Margarita Garcia-Vila, Sebastian Gayler, Gerrit Hoogenboom, Leslie A. Hunt, Roberto C. Izaurralde, Mohamed Jabloun, Curtis D. Jones, Kurt C. Kersebaum, Bruce A. Kimball, Ann-Kristin Koehler, Soora Naresh Kumar, Claas Nendel, Garry J. O’Leary, Jørgen E. Olesen, Michael J. Ottman, Taru Palosuo, P. V. Varra Prasad, Eckart Priesack, Thomas A. M. Pugh, Matthew Reynolds, Ehsan E. Rezaei, Reimund P. Rötter, Erwin Schmid, Mikhail A. Semenov, Iurii Shcherbak, Elke Stehfest, Claudio O. Stöckle, Pierre Stratonovitch, Thilo Streck, Iwan Supit, Fulu Tao, Peter Thorburn, Katharina Waha, Gerard W. Wall, Enli Wang, Jeffrey W. White, Joost Wolf, Zhigan Zhao, and Yan Zhu, “Similar estimates of temperature impacts on global wheat yield by three independent methods,” *Nature Climate Change*, December 2016, 6 (12), 1130–1136.

Lobell, David B. and Christopher B. Field, “Global scale climate–crop yield relationships and the impacts of recent warming,” *Environmental Research Letters*, March 2007, 2 (1), 014002. Publisher: IOP Publishing.

_ and Gregory P. Asner, “Climate and Management Contributions to Recent Trends in U.S. Agricultural Yields,” *Science*, February 2003, 299 (5609), 1032–1032. Publisher: American Association for the Advancement of Science Section: Brevia.

_ and Senthold Asseng, “Comparing estimates of climate change impacts from process-based and statistical crop models,” *Environmental Research Letters*, 2017, 12 (1), 015001.

_ , Graeme L. Hammer, Greg McLean, Carlos Messina, Michael J. Roberts, and Wolfram Schlenker, “The critical role of extreme heat for maize production in the United States,” *Nature Climate Change*, 2013, 3 (5), 497–501.

_ , J. Ivan Ortiz-Monasterio, Gregory P. Asner, Pamela A. Matson, Rosamond L. Naylor, and Walter P. Falcon, “Analysis of wheat yield and climatic trends in Mexico,” *Field Crops Research*, November 2005, 94 (2), 250–256.

_ , Michael J. Roberts, Wolfram Schlenker, Noah Braun, Bertis B. Little, Rod- erick M. Rejesus, and Graeme L. Hammer, “Greater Sensitivity to Drought Ac-
companies Maize Yield Increase in the U.S. Midwest,” *Science*, May 2014, **344** (6183), 516–519.

_ , Wolfram Schlenker, and Justin Costa-Roberts, “Climate Trends and Global Crop Production Since 1980,” *Science*, July 2011, **333** (6042), 616–620.

Matranga, Andrea, “The ant and the grasshopper: seasonality and the invention of agriculture,” 2017.

McIntosh, C. T and W. Schlenker, “Identifying Non-linearities In Fixed Effects Models,” 2006.

McMaster, G. S and W. W. Wilhelm, “Growing degree-days: one equation, two interpretations,” *Agricultural and Forest Meteorology*, 1997, **87** (4), 291–300.

Mendelsohn, Robert, “What Causes Crop Failure?,” *Climatic Change*, March 2007, **81** (1), 61–70.

_ , William D. Nordhaus, and Daigee Shaw, “The Impact of Global Warming on Agriculture: A Ricardian Analysis,” *The American Economic Review*, September 1994, **84** (4), 753–771.

Mérel, Pierre and Matthew Gammans, “Climate Econometrics: Can the Panel Approach Account for Long-Run Adaptation?,” *American Journal of Agricultural Economics*, 2021, n/a (n/a). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ajae.12200.

Mesinger, Fedor, Geoff DiMego, Eugenia Kalnay, Kenneth Mitchell, Perry C. Shafran, Wesley Ebisuzaki, Dušan Jovič, Jack Woollen, Eric Rogers, Ernesto H. Berbery, Michael B. Ek, Yun Fan, Robert Grumbine, Wayne Higgins, Hong Li, Ying Lin, Geoff Manikin, David Parrish, and Wei Shi, “North American Regional Reanalysis,” *Bulletin of the American Meteorological Society*, March 2006, **87** (3), 343–360.

Moore, Frances, “The Fingerprint of Anthropogenic Warming on Global Agriculture,” October 2020. Publisher: EarthArXiv.

Moore, Frances C. and David B. Lobell, “Adaptation potential of European agriculture in response to climate change,” *Nature Climate Change*, May 2014, *advance online publication.*
Lantz C. Baldos, and Thomas Hertel, “Economic impacts of climate change on agriculture: a comparison of process-based and statistical yield models,” *Environmental Research Letters*, 2017, 12 (6), 065008. Publisher: IOP Publishing.

Morgan, John J., “Use of Weather Factors in Short-Run Forecasts of Crop Yields,” *American Journal of Agricultural Economics*, 1961, 43 (5), 1172–1178. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.2307/1235568.

Moulton, Brent R., “Random group effects and the precision of regression estimates,” *Journal of Econometrics*, August 1986, 32 (3), 385–397.

Mukherjee, Monobina and Kurt Schwabe, “Irrigated Agricultural Adaptation to Water and Climate Variability: The Economic Value of a Water Portfolio,” *American Journal of Agricultural Economics*, 2015, 97 (3), 809–832. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1093/ajae/aau101.

Nelson, Gerald C., Hugo Valin, Ronald D. Sands, Petr Havlík, Helal Ahammad, Delphine Deryng, Joshua Elliott, Shinichiro Fujimori, Tomoko Hasegawa, Edwina Heyhoe, Page Kyle, Martin Von Lampe, Hermann Lotze-Campen, Daniel Mason d’Croz, Hans van Meijl, Dominique van der Mensbrugghe, Christoph Müller, Alexander Popp, Richard Robertson, Sherman Robinson, Erwin Schmid, Christoph Schmitz, Andrzej Tabeau, and Dirk Willenbockel, “Climate change effects on agriculture: Economic responses to biophysical shocks,” *Proceedings of the National Academy of Sciences*, March 2014, 111 (9), 3274–3279. Publisher: National Academy of Sciences Section: Social Sciences.

Newey, Whitney K. and Kenneth D. West, “A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix,” Technical Report, National Bureau of Economic Research 1986.

Nicholls, Neville, “Increased Australian wheat yield due to recent climate trends,” *Nature*, May 1997, 387 (6632), 484–485. Number: 6632 Publisher: Nature Publishing Group.

Olmstead, Alan L. and Paul W. Rhode, “Adapting North American wheat production to climatic challenges, 1839–2009,” *Proceedings of the National Academy of Sciences*, January 2011, 108 (2), 480–485. Publisher: National Academy of Sciences Section: Social Sciences.
Ortiz-Bobea, Ariel, “The Economic Impacts of Climate Change on Agriculture: Accounting for Time-invariant Unobservables in the Hedonic Approach,” Cornell University Applied Economics and Management Working Paper No. 2016-15, 2016.

_ , “The Role of Nonfarm Influences in Ricardian Estimates of Climate Change Impacts on US Agriculture,” American Journal of Agricultural Economics, 2019.

_ and Jesse Tack, “Is another genetic revolution needed to offset climate change impacts for US maize yields?,” Environmental Research Letters, 2018, 13 (12), 124009.

_ and Richard E. Just, “Modeling the Structure of Adaptation in Climate Change Impact Assessment,” American Journal of Agricultural Economics, 2013, 95, 244–251.

_ , Erwin Knippenberg, and Robert G. Chambers, “Growing climatic sensitivity of U.S. agriculture linked to technological change and regional specialization,” Science Advances, December 2018, 4 (12), eaat4343.

_ , Haoying Wang, Carlos M. Carrillo, and Toby R. Ault, “Unpacking the climatic drivers of US agricultural yields,” Environmental Research Letters, May 2019, 14 (6), 064003. Publisher: IOP Publishing.

_ , Toby R. Ault, Carlos M. Carrillo, Robert G. Chambers, and David B. Lobell, “The Historical Impact of Anthropogenic Climate Change on Global Agricultural Productivity,” arXiv:2007.10415 [econ, q-fin], July 2020. arXiv: 2007.10415.

_ , _ , _ , _ , and _ , “Anthropogenic climate change has slowed global agricultural productivity growth,” Nature Climate Change, April 2021, 11 (4), 306–312. Number: 4 Publisher: Nature Publishing Group.

Oury, Bernard, “Allowing for Weather in Crop Production Model Building,” Journal of Farm Economics, May 1965, 47 (2), 270–283. ArticleType: primary_article / Full publication date: May, 1965 / Copyright © 1965 Agricultural & Applied Economics Association.

Pace, R.K. and James P. LeSage, “A spatial Hausman test,” Economics Letters, December 2008, 101 (3), 282–284.

Pachauri, R. K., M. R. Allen, V. R. Barros, J. Broome, W. Cramer, R. Christ, J. A. Church, L. Clarke, Q. Dahe, P. Dasgupta, N. K. Dubash, O. Edenhofer, I. Elgizouli, C. B. Field, P. Forster, P. Friedlingstein, J. Fuglestvedt, L. Gomez-Echeverri, S. Hallegatte, G. Hegerl, M. Howden, K. Jiang, B. Jimenez Cisneroz, V. Kattsov, H. Lee, K. J. Mach, J. Marotzke, M. D. Mastrandrea,
Palmquist, Raymond B., “Land as a Differentiated Factor of Production: A Hedonic Model and Its Implications for Welfare Measurement,” *Land Economics*, February 1989, 65 (1), 23–28.

Porter, John R., Liyong Xie, Andrew J. Challinor, Kevern Cochrane, S. Mark Howden, Muhammad Mohsin Iqbal, David B. Lobell, and Maria Isabel Travassao, “Food security and food production systems,” 2014. Publisher: Cambridge University Press.

Quiggin, John and John K. Horowitz, “The Impact of Global Warming on Agriculture: A Ricardian Analysis: Comment,” *The American Economic Review*, September 1999, 89 (4), 1044–1045.

Ramankutty, Navin, Amato T. Evan, Chad Monfreda, and Jonathan A. Foley, “Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000,” *Global Biogeochemical Cycles*, 2008, 22 (1). _eprint:_ https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2007GB002952.

Randhir, Timothy O. and Thomas W. Hertel, “Trade Liberalization as a Vehicle for Adapting to Global Warming,” *Agricultural and Resource Economics Review*, October 2000, 29 (2), 159–172. Publisher: Cambridge University Press.

Rao, A. C. S., J. L. Smith, V. K. Jandhyala, R. I. Papendick, and J. F. Parr, “Cultivar and Climatic Effects on the Protein Content of Soft White Winter Wheat,” *Agronomy Journal*, 1993, 85 (5), 1023–1028. _eprint:_ https://acsess.onlinelibrary.wiley.com/doi/pdf/10.2134/agronj1993.00021962008500050013x.

Ray, Deepak K. and Jonathan A. Foley, “Increasing global crop harvest frequency: recent trends and future directions,” *Environmental Research Letters*, November 2013, 8 (4), 044041. Publisher: IOP Publishing.
Réaumur, R. A., “Observations du thermomètre faites pendant l’année MDCCXXXV comparées à celles qui ont été faites sous la ligne à l’Isle-de-France, à Alger et en quelques-unes de nos Isles de l’Amérique,” Mémoires de l’Académie Royal des Sciences, 1735, pp. 545–76.

Reilly, J., F. Tubiello, B. McCarl, D. Abler, R. Darwin, K. Fuglie, S. Hollinger, C. Izaurralde, S. Jagtap, J. Jones, L. Mearns, D. Ojima, E. Paul, K. Paustian, S. Riha, N. Rosenberg, and C. Rosenzweig, “U.S. Agriculture and Climate Change: New Results,” Climatic Change, March 2003, 57 (1), 43–67.

Riahi, Keywan, Detlef P. van Vuuren, Elmar Kriegler, Jae Edmonds, Brian C. O’Neill, Shinichiro Fujimori, Nico Bauer, Katherine Calvin, Rob Dellink, Oliver Fricko, Wolfgang Lutz, Alexander Popp, Jesus Crespo Cuaresma, Samir Ke, Marian Leimbach, Leiwen Jiang, Tom Kram, Shilpa Rao, Johannes Emmerling, Kristie Ebi, Tomoko Hasegawa, Petr Havlik, Florian Humbmenöder, Lara Aleluia Da Silva, Steve Smith, Elke Stehfest, Valentina Bosetti, Jiyong Eom, David Gernaat, Toshihiko Masui, Joeri Rogelj, Jessica Streferl, Laurent Drouet, Volker Krey, Gunnar Luderer, Mathijs Harmsen, Kiyoshi Takahashi, Lavinia Baumstark, Jonathan C. Doelman, Mikiko Kainuma, Zbigniew Klimont, Giacomo Marangoni, Hermann Lotze-Campen, Michael Obersteiner, Andrzej Tabeau, and Massimo Tavoni, “The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview,” Global Environmental Change, January 2017, 42, 153–168.

Ritchie, J. T., DS NE S MITH, J. Hanks, and J. T. Ritchie, “Temperature and crop development,” Agronomy (EUA), 1991, 31.

Roberts, Michael J., Noah O. Braun, Thomas R. Sinclair, David B. Lobell, and Wolfram Schlenker, “Comparing and combining process-based crop models and statistical models with some implications for climate change,” Environmental Research Letters, 2017, 12 (9), 095010.

_ , Wolfram Schlenker, and Jonathan Eyer, “Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change,” American Journal of Agricultural Economics, May 2012, p. aas047.

Rodell, M., P. R. Houser, U. Jambor, J. Gottschalck, K. Mitchell, C.-J. Meng, K. Arsenault, B. Cosgrove, J. Radakovich, M. Bosilovich, J. K. Entin, J. P. Walker, D. Lohmann, and D. Toll, “The Global Land Data Assimilation System,”
Rosen, Sherwin, “Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition,” Journal of Political Economy, January 1974, 82 (1), 34–55.

Rosenzweig, Cynthia and Martin L. Parry, “Potential impact of climate change on world food supply,” Nature, 1994, 367, 133–138.

_ , Joshua Elliott, Delphine Deryng, Alex C. Ruane, Christoph Müller, Almut Arneth, Kenneth J. Boote, Christian Folberth, Michael Glotter, Nikolay Khabarov, Kathleen Neumann, Franziska Piontek, Thomas A. M. Pugh, Erwin Schmid, Elke Stehfest, Hong Yang, and James W. Jones, “Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison,” Proceedings of the National Academy of Sciences, March 2014, 111 (9), 3268–3273.

Rötter, Reimund P., Timothy R. Carter, Jørgen E. Olesen, and John R. Porter, “Crop–climate models need an overhaul,” Nature Climate Change, July 2011, 1 (4), 175–177. Number: 4 Publisher: Nature Publishing Group.

Sacks, William J., Delphine Deryng, Jonathan A. Foley, and Navin Ramankutty, “Crop planting dates: an analysis of global patterns,” Global Ecology and Biogeography, 2010, 19 (5), 607–620.

Schickele, Rainer, “Farm Business Survival under Extreme Weather Risks,” American Journal of Agricultural Economics, 1949, 31 (4_Part_2), 931–943. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.2307/1233760.

Schlenker, Wolfram and Michael J. Roberts, “Nonlinear Effects of Weather on Corn Yields,” Review of Agricultural Economics, 2006, 28 (3), 391–398.

_ and _ , “Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change,” Proceedings of the National Academy of Sciences, September 2009, 106 (37), 15594–15598.

_ and _ , “Reply to Meerburg et al.: Growing areas in Brazil and the United States with similar exposure to extreme heat have similar yields,” Proceedings of the National Academy of Sciences, October 2009, 106 (43), E121–E121.

_ , _ , and David B. Lobell, “US maize adaptability,” Nature Climate Change, August 2013, 3 (8), 690–691. Number: 8 Publisher: Nature Publishing Group.
_, W. Michael Hanemann, and Anthony C. Fisher, “Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach,” *The American Economic Review*, March 2005, *95* (1), 395–406.

_, _, and _, “The Impact of Global Warming on U.S. Agriculture: An Econometric Analysis of Optimal Growing Conditions,” *Review of Economics and Statistics*, February 2006, *88* (1), 113–125.

Seifert, Christopher A. and David B. Lobell, “Response of double cropping suitability to climate change in the United States,” *Environmental Research Letters*, January 2015, *10* (2), 024002. Publisher: IOP Publishing.

Seneviratne, Sonia I., Thierry Corti, Edouard L. Davin, Martin Hirschi, Eric B. Jaeger, Irene Lehner, Boris Orlowsky, and Adriaan J. Teuling, “Investigating soil moisture–climate interactions in a changing climate: A review,” *Earth-Science Reviews*, May 2010, *99* (3), 125–161.

Seo, S. Niggol and Robert Mendelsohn, “Measuring impacts and adaptations to climate change: a structural Ricardian model of African livestock management,” *Agricultural Economics*, March 2008, *38* (2), 151–165.

Severen, Christopher, Christopher Costello, and Olivier Deschênes, “A Forward-Looking Ricardian Approach: Do land markets capitalize climate change forecasts?,” *Journal of Environmental Economics and Management*, May 2018, *89*, 235–254.

Shaw, Lawrence H., “The Effect of Weather on Agricultural Output: A Look at Methodology,” *Journal of Farm Economics*, February 1964, *46* (1), 218–230. ArticleType: primary_article / Full publication date: Feb., 1964 / Copyright © 1964 Agricultural & Applied Economics Association.

Sheffield, Justin, Gopi Goteti, and Eric F. Wood, “Development of a 50-Year High-Resolution Global Dataset of Meteorological Forcings for Land Surface Modeling,” *Journal of Climate*, July 2006, *19* (13), 3088–3111. Publisher: American Meteorological Society.

Shew, Aaron M., Jesse B. Tack, Lawton L. Nalley, and Petronella Chaminuka, “Yield reduction under climate warming varies among wheat cultivars in South Africa,” *Nature Communications*, September 2020, *11* (1), 4408. Number: 1 Publisher: Nature Publishing Group.
Siebert, Stefan, Felix T. Portmann, and Petra Döll, “Global Patterns of Cropland Use Intensity,” Remote Sensing, July 2010, 2 (7), 1625–1643. Number: 7 Publisher: Molecular Diversity Preservation International.

Simonsohn, Uri, Joseph P. Simmons, and Leif D. Nelson, “Specification Curve: Descriptive and Inferential Statistics on All Reasonable Specifications,” SSRN Scholarly Paper ID 2694998, Social Science Research Network, Rochester, NY October 2019.

Soares, José C., Carla S. Santos, Susana M. P. Carvalho, Manuela M. Pintado, and Marta W. Vasconcelos, “Preserving the nutritional quality of crop plants under a changing climate: importance and strategies,” Plant and Soil, October 2019, 443 (1), 1–26.

Solon, Gary, Steven J. Haider, and Jeffrey M. Wooldridge, “What Are We Weighting For?,” Journal of Human Resources, 2015, 50 (2), 301–316.

Stallings, James L., “Weather Indexes,” Journal of Farm Economics, February 1960, 42 (1), 180–186. ArticleType: primary_article / Full publication date: Feb., 1960 / Copyright © 1960 Agricultural & Applied Economics Association.

, “A Measure of the Influence of Weather on Crop Production,” Journal of Farm Economics, December 1961, 43 (5), 1153–1160. ArticleType: primary_article / Issue Title: Proceedings Number / Full publication date: Dec., 1961 / Copyright © 1961 Agricultural & Applied Economics Association.

Tack, Jesse, Andrew Barkley, and Lawton Lanier Nalley, “Effect of warming temperatures on US wheat yields,” Proceedings of the National Academy of Sciences, June 2015, 112 (22), 6931–6936.

Tao, Fulu, Masayuki Yokozawa, Jiyuan Liu, and Zhao Zhang, “Climate–crop yield relationships at provincial scales in China and the impacts of recent climate trends,” Climate Research, November 2008, 38 (1), 83–94.

, , Yinlong Xu, Yousay Hayashi, and Zhao Zhang, “Climate changes and trends in phenology and yields of field crops in China, 1981–2000,” Agricultural and Forest Meteorology, August 2006, 138 (1), 82–92.

Thornton, Peter E., Michele M. Thornton, Benjamin W. Mayer, Nate Wilhelmi, Yaxing Wei, Ranjeet Devarakonda, and Robert B. Cook, “Daymet: Daily Surface Weather Data on a 1-km Grid for North America, Version 2.,” Technical Report, Oak Ridge National Lab.(ORNL), Oak Ridge, TN (United States) 2014.
Timmins, Christopher, “Endogenous Land use and the Ricardian Valuation of Climate Change,” *Environmental and Resource Economics*, December 2005, 33 (1), 119–142.

Waha, Katharina, Jan Philipp Dietrich, Felix T. Portmann, Stefan Siebert, Philip K. Thornton, Alberte Bondeau, and Mario Herrero, “Multiple cropping systems of the world and the potential for increasing cropping intensity,” *Global Environmental Change*, September 2020, 64, 102131.

Wang, Jen Yu, “A Critique of the Heat Unit Approach to Plant Response Studies,” *Ecology*, October 1960, 41 (4), 785–790.

Welch, Jarrod R., Jeffrey R. Vincent, Maximilian Auffhammer, Piedad F. Moya, Achim Dobermann, and David Dawe, “Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures,” *Proceedings of the National Academy of Sciences*, August 2010, 107 (33), 14562–14567.

Wu, Wenbin, Qiangyi Yu, Liangzhi You, Kevin Chen, Huajun Tang, and Jian-guo Liu, “Global cropping intensity gaps: Increasing food production without cropland expansion,” *Land Use Policy*, July 2018, 76, 515–525.

Xia, Youlong, Kenneth Mitchell, Michael Ek, Justin Sheffield, Brian Cosgrove, Eric Wood, Lifeng Luo, Charles Alonge, Helin Wei, Jesse Meng, Ben Livneh, Dennis Lettenmaier, Victor Koren, Qingyun Duan, Kingtse Mo, Yun Fan, and David Mocko, “Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products,” *Journal of Geophysical Research*, February 2012, 117 (D3), D03109.