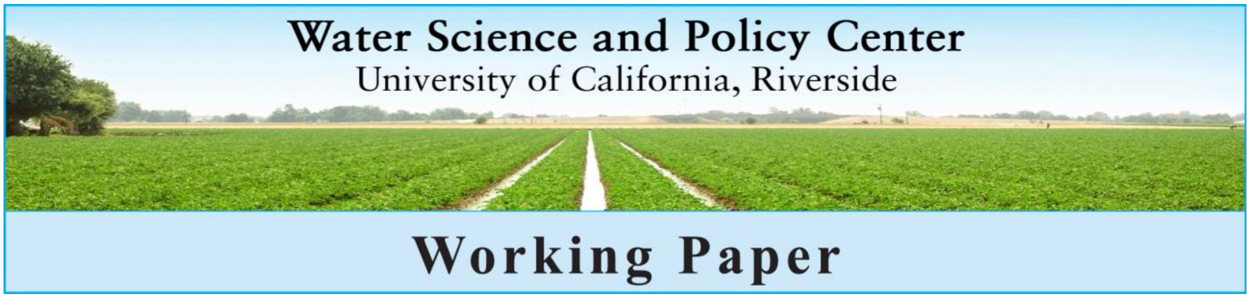

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Science and Economic Aspects of Impact of and Adaptation to Climate Change Induced Water Scarcity in Western US Agriculture

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Abstract

This paper reviews three critical dimensions of climatic impacts to agriculture, which are rarely discussed in a single document: meteorological (global climate models), agronomic (process-based and production function), and economic (mathematical programming and econometric) modeling. We also discuss studies on farmer adaptations, particularly why farmers choose certain adaptations over others. This is followed by a brief assessment of model results in the southwestern United States. Crop simulation analyses suggest that higher-value crops in the region will be most sensitive to climatic changes, while economic analyses suggest that higher crop value may make the crop more attractive for farming under future climatic stress. Such tensions between climate sensitivity and crop value make the study of adaptation in the region all the more critical.

Keywords: Climate change, water scarcity, impact, adaptation, agriculture, economics, simulation, production function, California, Southwestern United States

1. Introduction

The hydrologic cycle of the western United States will likely be impacted by climatic changes. Temperature increases, more frequent extreme precipitation events, snowpack decline, shifted timing of peak snowpack and runoff, and a decline in groundwater recharge have been observed over the past century, and are projected for the next one. High-elevation mountains in the western United States receive the majority of their annual precipitation as winter and spring snow (Clow 2010; Serreze et al. 1999; Hoerling et al. 2013). Changes in timing of snowmelt and snowmelt-driven runoff will impact the timing of water availability. In particular, much of the southwestern United States is dependent on Colorado River water. Any changes in runoff and streamflow will have major impacts on water resources. This may exacerbate reliance on groundwater, which is experiencing a decline in recharge due to climatic changes and with the increased pumping by users faced with increased surface water scarcity. Coupling this with the fact that the southwestern United States region is a major agricultural producer with parts almost entirely dependent on irrigation water – agriculture accounts for 79 percent of southwestern water withdrawals (Frisvold et al. 2013) – some have identified parts of the Southwest as highly vulnerable to climate change (Jackson et al. 2012). The duration of the growing season has increased over the last century. The average growing season across the Southwest during 2001-

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2010 was 17 days longer than the twentieth century average, and one month longer than that of the first decade of the twentieth century (Hoerling et al. 2013). Taking into account that the Southwest produces more than half of the nation's high-value specialty crops, the entire nation is ultimately vulnerable (Frisvold et al. 2013).

On a global scale, Zilberman et al. (2004) suggest that climate change will cause a shift of agriculture away from the Equator and towards the Poles. Several scholars have found that climate impacts on agriculture threaten food security, particularly in developing countries (Lobell et al. 2008; Fischer et al. 2005, Parry et al. 2004; Chipanshi et al. 2003; Winters et al. 1998). Frisvold et al. (2013) suggest that many of the costs to agriculture will be adjustment costs (e.g., developing infrastructure in new areas that were previously climatically unsuitable for crop growth, adjusting the timing of operations due to the shift in runoff). Adaptation costs (e.g., shifting crop mix, rotation patterns, water-efficient irrigation) must also be taken into account. Some suggest that pest management will need to increase with climate change (Frisvold et al. 2013; Hayhoe et al. 2004). In addition, there will be yield costs related to the loss in quality and quantity from climatic changes (Hayhoe et al. 2004).

It is important to study how adaptations could improve the situation in order to inform policy. It is also important to understand what drives technology adoption behavior among farmers in order to develop appropriate incentives to encourage adaptation as well as mitigation. This paper is distinct because it is a holistic review of climatic impacts on agriculture. It begins with scientific results on the impact of climatic changes to the hydrologic cycle. It then discusses methodologies for studying the climatic impacts to crop development and yield, followed by economic methodologies. This is followed by a classification of adaptation strategies. The paper ends with a summary of the specific impacts to the southwestern United States.

2. Climate impacts on the hydrologic cycle

The climate of the American Southwest is generally described as warm and dry, with local variation. Southern California generally exhibits a Mediterranean climate with long, dry summers and wet winters (Dettinger et al. 2011). California, in particular, experiences large variations in annual precipitation and streamflow relative to the rest of the United States; a small number of large storms account for most of its annual precipitation (Dettinger et al. 2011). Like California, Arizona exhibits a range of climates. Parts of Arizona (e.g., the southeast) have long, dry summers and a bi-modal precipitation regime (i.e., wet winters and summer monsoonal periods) (Serrat-Capdevila et al. 2007). Precipitation in both these areas tends to exhibit extreme behavior, i.e., short-lived and intense events (Dettinger et al. 2011; Serrat-Capdevila et al. 2007). Winter rains are important in both regions, and a key component of groundwater and surface recharge (Green et al. 2011; Serrat-Capdevila et al. 2007; Cayan et al. 1998).

Climate – as observed through temperature and precipitation variables – in the Southwest has changed in the historic record, and is projected to change through several general circulation model (GCM) projections. Average daily temperature in the Southwest for the previous decade (2001-2010) has been higher than any decade observed in the previous century (Hoerling et al. 2013). The report by Hoerling et al. (2013) also indicates with high confidence that fewer cold waves and more heat waves occurred in this previous decade as compared to their average occurrences across the twentieth century. In addition, Hoerling et al. (2013) assert with medium-to-high confidence that the period since 1950 has been warmer than any period in the previous six centuries for the Southwest. Although precipitation is a key climatic variable, it does not exhibit any clear trends in the Southwest over the previous century (Hoerling et al. 2013; Barnett et al. 2008; Trenberth et al. 2007), which suggests that projections of precipitation are less reliable than those of temperature.

Precipitation is the only process that is both a key climatic change variable and a key component of the hydrologic cycle[2]. Precipitation impacts groundwater runoff, streamflow, and groundwater. Precipitation falling as snow is converted to rain with rising temperatures, in turn affecting the timing of runoff and streamflow dynamics. Temperature also directly impacts snowpack, causing earlier snowmelt. Held and Soden (2006) indicate that there are several robust responses to the hydrologic cycle, which are consequences of the increase in lower-tropospheric water vapor.[3] Barnett et al. (2008) suggest that up to 60 percent of climate-related trends in streamflow, winter temperature, and snowpack in the western United States from 1950-1999 are human-induced.

The following subsection is organized into broad climatic impacts to the hydrologic cycle, namely impacts to precipitation, groundwater, snow dynamics, and streamflow. A basic discussion of general circulation models and temperature changes precedes this.

3. GCMs

Of the tools used to simulate climatic changes, general circulation models (GCMs) are the most sophisticated and widely used in current research (Green et al. 2011). These are three-dimensional models based on complex fluid dynamics equations used for weather modeling (e.g., Navier-Stokes equations[4]), since climate is determined by the general circulation of the atmosphere. According to Green et al. (2011), GCMs simulate extreme warm temperatures, cold air outbreaks and frost days reasonably well, while simulation of all precipitation variables is less consistent. Regional circulation models (RCMs) generally provide more realistic patterns of mean and extreme precipitation at the regional scale (Dominguez et al. 2012). There are additional methodological challenges when coupling GCM output with hydrologic models (Scibek and Allen 2006; Toews and Allen 2009).

In addition to distinct GCM research institutions, groups such as the Program for Climate Model Diagnosis and Inter-comparison have been established to compare the accuracy of the different GCMs. Since GCMs have computational grids generally on the order of 200km, most studies “downscale” GCM data to local scales. There are two general downscaling techniques: (1) dynamic climate modeling, which involves a higher resolution RCM within a GCM; and (2) statistical downscaling, which combines existing and past empirical knowledge to address the disparity between broad GCM predictions and meteorological observations (Green et al. 2011). There is still quite a bit of uncertainty between predictions by GCMs from different research groups, suggesting that the output from GCMs should be taken as projections rather than predictions. As Allen and Ingram (2002) state, “We cannot hope to predict the exact climate of 2050, still less the weather on a particular day, but we can assess the relative likelihood of different long-term trends…”

[2] While temperature is a driver of the hydrologic cycle, unlike precipitation, it is not a component of it.

[3] These responses include decrease in convective mass fluxes, increase in horizontal moisture transport, enhancement of pattern of evaporation minus precipitation and its temporal variance, and the decrease in horizontal sensible heat transport in the extratropics (Held and Soden 2006).

[4] Navier-Stokes are equations of fluid dynamics, often used to model weather patterns.

The projected impacts of climatic variables (i.e., precipitation and temperature) on the hydrologic cycle are often undertaken by linking GCM output to a hydrologic model. The Variable Infiltration Capacity (VIC) is a common hydrologic model that accounts for fluxes of water and energy at the land surface (Das et al. 2011; Christensen and Lettenmaier 2007; Mote et al. 2005). Another modeling framework is the Groundwater Modeling System (Serrat-Capdevila et al. 2007).

4. Temperature

The NOAA National Climatic Data Center suggests that in 2012 the average temperature for the contiguous United States was 55.3°F, roughly 3.2°F above the twentieth-century average and 1.0°F above the previous record in 1998 (Osbourne and Crouch 2012). This indicates that 2012 is thus far the warmest year on record for the contiguous United States. This is consistent with the high confidence findings that 2001-2010 was the warmest decade in the Southwest over the past 11 decades (Hoerling et al. 2013). The period since 1950 has been warmer than any comparable period in the last 600 years (Hoerling et al. 2013). Robeson (2004) and Trenberth et al. (2007) found intense warming of the lowest daily minimum temperatures over western and central North America. The average annual temperature has increased by 0.9°C from 1901-2010 in the Southwest (Hoerling et al. 2013). On a global scale, the IPCC 5th Assessment Report indicates that the average temperature has increased by 0.12°C per decade from 1951-2012 (Hartmann et al. 2013). Barnett et al. (2008) find that daily minimum temperatures in winter (January-March) have increased between 0.28-0.43°C per decade from 1950-1999. Trenberth et al. (2007) further suggest that the cold tails of temperature distributions have warmed more than the warm tails across the globe over the latter half of the twentieth century, and into the twenty-first century. The observed trends in increased winter and spring temperatures over the latter part of the twentieth century (roughly the 1970s) is very unlikely to have been caused by natural variability alone (Barnett et al. 2008; Cayan et al. 2006).

Temperatures are projected to rise over the twenty-first century with high confidence (Cayan et al. 2013). Cayan et al. (2006) have a low range projected warming of 1.7-3.0°C between 2000 and 2100, and high range of 4.4-5.8°C. Using an ensemble of 15 GCMs, Cayan et al. (2013) find that, in the early part of the twenty-first century, there is relatively little disparity between the warming produced by the low and high emissions scenarios. However, the disparity in warming between scenarios starts to increase in the middle of the twenty-first century, and doubles by the end of the century (Cayan et al. 2006; Hayhoe et al. 2004). Christensen and Lettenmaier (2007) modeled the climatic impacts on hydrology of the Colorado River Basin using an ensemble of 11 GCMs. The mean temperature for the A2 emissions scenario for 2010-2099 ranges from 1.2-4.4°C, and 1.3-2.7°C for the B1 scenario.

5. Precipitation

Based on the current scientific literature, it is clear that both the detection and attribution[5] of temperature changes over the twentieth century (and the first decade of the twenty-first century) exhibit more robust trends than the highly episodic precipitation changes over this period (Costa-Cabral et al. 2013). Precipitation patterns are fundamentally more complex and variable than

[5] According to the IPCC Fourth Assessment Report, detection studies demonstrate that the climate has changed in some defined statistical sense, without providing a reason for that change. Attribution studies establish the most likely causes for detected change with some defined level of confidence (IPCC 2007, pg. 102-3).

temperature patterns, with a high degree of variability across space and time. This is exemplified by the inconsistency among global precipitation models in detecting the per-decade precipitation changes over the last century. Adding to the complication, existing datasets on precipitation may not have sufficient coverage to estimate total precipitation at either global or regional scales (Wan et al. 2013). Thus, there is only medium confidence in the direction of average global precipitation change proceeding 1950 (Hartmann et al. 2013). It is worth noting that subsequently discussed studies on crop yields and farmer adaptations are compounding the uncertainty in precipitation estimates (Ceglar and Kajfež-Bogataj 2012; Allen and Ingram 2002), indicating that highly specific policy recommendations based on these estimates should be followed with caution.

Nonetheless, general precipitation trends have been detected for the twentieth century at global and regional scales. In general, significant, large-scale correlations have been observed between precipitation and monthly mean temperature, which exhibit an inverse relationship (Trenberth et al. 2007). Thus, during the warm season, higher temperatures and lower precipitation tend to occur simultaneously (and vice versa). This is a cause for concern in the southwestern United States, which has experienced the most rapid rate of warming in the nation (Karl, Melillo, and Peterson 2009). While annual precipitation has increased over the period 1901-2005 for most of North America, it has decreased in the southwestern United States (and northwest Mexico and Baja California Peninsula) (Trenberth et al. 2007). Consistent with scientific theory, empirical research suggests that warmer climates, such as those projected for the Southwest, will lead to more extreme precipitation intensity and frequency (Allan and Soden 2008; Trenberth et al. 2007), particularly during the winter season (Dominguez et al. 2012; Maurer 2007; Cayan et al. 2006). Since annual precipitation is projected to decline[6] (Trenberth et al. 2007), more extreme events do *not* translate into higher total rainfall for a given year. Instead, it is projected that light precipitation – an important source for soil moisture and groundwater recharge – will concomitantly decline.

5.1 Drought

Drought can be defined as a prolonged absence or marked deficiency in precipitation (Heim 2002). Between 1901 and 2010, the areal extent of drought increased in the southwestern United State (Hoerling et al. 2013). In terms of land area affected, the second largest drought occurred quite recently during 2001-2010 (Hoerling et al. 2013). Across the western United States, the spring of 2004 was unusually warm and dry (Pagano et al. 2004); however, in Arizona the winter of 2005-2006 ranked the driest in the instrumental record (since 1895) (Goodrich and Ellis 2008). Pielke et al. (2005) suggest that the state of Colorado is more vulnerable to drought at present, due to precipitation deficits, than in the past. Some have attributed the increasing expanse of drought, particularly in the previous decade, to warmer temperatures (Dai 2011). Others have suggested that it is due to changes in atmospheric circulation (McCabe et al. 2004; Hoerling and Kumar 2003).

5.2 Precipitation extremes

The IPCC Fifth Assessment Report states that it is likely that the frequency of heavy precipitation events has increased in more regions across the globe than it has decreased

[6] This is a robust finding in the IPCC Fourth Assessment Report.

(Hartmann et al. 2013). This is supported by other studies[7], which find an increase in both the intensity (Dominguez et al. 2012) and frequency (Emori and Brown 2005) of precipitation extremes. Trenberth et al. 2007 present the mechanism behind warmer temperatures leading to an increase in extreme precipitation events. They suggest that the sea surface temperature has changed and this has led to an increase in atmospheric water vapor– approximately a 5 percent increase in atmospheric water vapor over the twentieth century. This, in turn, has increased precipitation intensity and the risk of heavy rain and snow events. At the global level, Alexander et al. (2006) find that the percentage contribution to total annual precipitation from very wet days is greater in recent decades than earlier decades. Groisman et al. (2004) find statistically significant increases in heavy and very heavy precipitation in the contiguous United States. In addition, they find that there is an increasing proportion of extreme precipitation events in total precipitation quantities. Studies in the western United States project an increase in future extreme precipitation intensity (Dominguez et al. 2012). Using the multi-model mean from eight dynamically downscaled simulations, Dominguez et al. (2012) find a 12.8 percent future increase in the 20-year projection, and at 14.4 percent increase in the 50-year projection of the intensity of heavy precipitation events. Furthermore, this increase takes place during winter. In addition, Raisanen (2005) finds a link between extreme and mean precipitation; wet extremes become more severe in places where mean precipitation increases with an inverse result for dry extremes.

5.3 Precipitation attribution studies

There are mixed conclusions from attribution studies with respect to precipitation extremes and averages. Min et al. (2011) is widely cited as evidence that human activities have accelerated precipitation extremes in the Northern Hemisphere. They use an optimal fingerprinting technique to analyze observed and multi-model projected changes during the latter half of the twentieth century. They also suggest that GCMs may underestimate the frequency and magnitude of extreme precipitation events in projections. Zhang et al. (2007) use an ensemble of 14 GCMs to study the observed trend in mean monthly precipitation over the twentieth century, averaged over latitudinal bands. They find that human activity has influenced average precipitation within latitudinal bands. It is interesting that although Barnett et al. (2008) find an anthropogenic contribution explaining roughly 60 percent of the trends in river flow, winter air temperature, and snowpack in the latter half of the twentieth century, they do not find an anthropogenic contribution for precipitation trends in the same nine western states during this period. Hoerling, Eischeid, and Perlwitz (2010) corroborate this finding using two ensemble suites of GCMs. Specifically, they do not find an anthropogenic link to the recent dryness over the Southwest, and, rather, find that it is associated with natural decadal coolness in tropical Pacific sea-surface temperatures. Overall, these studies suggest that strong evidence for annual averages or extremes in precipitation attributed to human production of GHGs is still lacking for the southwestern United States. However, some studies in the region suggest that *seasonal* variability in precipitation has increased more than that explained from natural variability in the latter half of the twentieth century (Goodrich and Ellis 2008).

[7] Studies could be examining the frequency of very heavy precipitation, an upper threshold of daily precipitation events, total number of days with precipitation greater than a threshold, and annual maximum precipitation based on one-day or five-day consecutive totals, etc. (Chu et al. 2010).

6. Groundwater

Groundwater is a reliable source of water use and storage for agriculture. Indeed groundwater in the phreatic zone (i.e., the most saturated area of an aquifer) comprises 30 percent of global freshwater resources (UNESCO 2008). While the most obvious impact of climate changes on the hydrologic cycle are changes in precipitation (rain and snow) and surface water levels (e.g., streamflow), there are potential changes to both the quality and quantity of groundwater as well, particularly since precipitation and surface water interactions are the main sources of aquifer recharge (Green et al. 2011). There is no standard response of aquifers to climatic changes (i.e., changes in precipitation, temperature, and CO_2) as the response to these variables depends on aquifer depth[8], whether it is confined or unconfined, spatial geography, and direct connections with the surface (Barco et al. 2010; Kundzewicz et al. 2007; Hanson, Dettinger and Newhouse 2006). However, scientific theory supports general relationships with these climate variables[9], particularly in agricultural settings. Light precipitation tends to increase groundwater recharge, whereas the impacts to recharge from heavy rains are mixed[10] (Kundzewicz and Döll 2009; Hanson, Dettinger and Newhouse 2006). Ficklin et al. (2010) present temperature and CO_2 dynamics for irrigated agriculture in the semi-arid Central Valley of California. Temperature increases tend to increase plant evapotranspiration, causing an increase in irrigation water demand, in turn causing a decrease in groundwater recharge. Increases in atmospheric CO_2 concentration tend to have two opposing effects: (1) increase in plant water use efficiency leading to lower irrigation water use, in turn increasing groundwater recharge; and (2) increase in plant growth leading to higher irrigation water use, in turn decreasing groundwater recharge (Ficklin et al. 2010). In addition to the climate impacts on the level of recharge, groundwater quality may also be impacted. The potential for saltwater intrusion from neighboring saline aquifers increases as the recharge rate declines, particularly in semi-arid and coastal regions (Kundzewicz et al. 2007; Chen et al. 2004). Also, following heavy precipitation events, the transport of pathogens to groundwater is accelerated (Kundzewicz et al. 2007). Groundwater recharge dynamics in the southwestern United States are also impacted by climate-induced snowmelt. Earman et al. (2006) find that snowmelt provides between 40 and 70 percent of groundwater recharge at study sites in the Southwest, although only 25-50 percent of average annual precipitation falls as snow.

There have been different approaches used to assess the climatic impacts on groundwater. Serrat-Capdevila et al. (2007) use the results from an ensemble of 17 GCMs to study the relationship between projected average annual precipitation changes and groundwater recharge in the San Pedro Basin in Arizona. Their results indicate that recharge in the San Pedro Basin will decline. Ficklin et al. (2010) explore the relationship among average daily temperature, atmospheric CO_2, and groundwater for irrigated agriculture in the semi-arid Central Valley (CA). It is particularly interesting that their results are crop-dependent. For example, groundwater recharge declines while growing alfalfa and almonds with increases in CO_2 and temperature,

[8] There is evidence that deeper aquifers react to long-term climate changes, whereas shallow aquifers react more to short-term changes (Kundzewicz and Döll 2009).

[9] In addition to precipitation, temperature and carbon dioxide, rising sea levels may also impact groundwater recharge (Kundzewicz and Döll 2009).

[10] Increased magnitude and frequency of heavy precipitation events may recharge (alluvial) aquifers via inundation in semi-arid and arid areas. In some soil types, recharge via inundation is low (e.g., Sahel). And, in sub-humid and humid areas infiltration capacity of the soil may be exceeded, resulting in decreased groundwater recharge (Kundzewicz and Döll 2009).

while recharge increases while growing tomatoes under these conditions. This disparity is caused by root depth. Alfalfa and almonds, as perennials, have constant root depths, which allow these crops to consume more water during the early growth cycle. Tomatoes are annuals and have shallower roots in the early stages of growth. Barco et al. (2010) take a different approach and explore how atmospheric circulation patterns are related to both groundwater and precipitation for Southern California. They find a relationship between El Niño Southern Oscillation (ENSO) and both precipitation and groundwater, although the extent of this relationship ultimately depends on aquifer characteristics. Hanson, Dettinger and Newhouse (2006) similarly assess the relationship with atmospheric circulation patterns, though they extend the hydrologic variables to include time series of streamflow and tree-ring indices. They find that California hydrologic variables have more variation associated with the Pacific Decadal Oscillation (PDO) and ENSO, while Arizona hydrologic variables have more variation associated with the North American Monsoon (NAM). This suggests that groundwater levels in each state are associated with particular atmospheric circulation patterns.

7. Snow accumulation and dynamics

Like groundwater, snow is a critical source of water storage. Maurer et al. (2007) suggest that snowpack is the "single largest" storage of water in the state of California. In high-elevation mountain areas in the western United States, snow accounts for the largest percentage of annual winter and spring precipitation (Clow 2010; Serreze et al. 1999). The quantity of snow is measured in three important ways: snowpack[11], snow water equivalent[12], and snowfall. Based on observational studies, there is widespread agreement that snowpack in the western United States has been declining in recent years (Kapnick and Hall 2012; Abatzoglu 2011; Pederson et al. 2011; Svoma 2011; Clow 2010; Minder 2010; Kapnick and Hall 2010; Barnett et al. 2008; Pierce et al. 2008; Mote et al. 2005, Regonda et al. 2004). These studies attribute this decrease to both natural (Kapnick and Hall 2012; Abatzoglu 2011; Svoma 2011; Clow 2010; Minder 2010; Kapnick and Hall 2010; Mote et al. 2005) and human-induced (Pederson et al. 2011; Barnett et al. 2008; Pierce et al. 2008) causes. Some studies of the western United States have focused on snowfall directly, with conflicting results. While some do not find statistically significant trends in snowfall patterns over the twentieth century (Christy 2012; Christy and Hnilo 2010), others find a clear reduction in precipitation falling as snow with a concomitant increase in precipitation falling as rain (Knowles et al. 2006; Regonda et al. 2005). Still other observational studies have focused on timing aspects. Peak snow mass timing has shifted to earlier in the winter season (Kapnick and Hall 2010), while increased winter time melting has been observed (Abatzoglu 2011; Clow 2010; Mote et al. 2005), particularly during the late winter season (Kapnick and Hall 2012). An advance in the timing of snowmelt-driven streamflow has also been observed (Stewart et al. 2005).

The observed spatial and temporal changes in snow characteristics have been attributed to regional-scale warming (Kapnick and Hall 2012; Pederson et al. 2011; Minder 2010; Mote et al. 2005), precipitation patterns (Svoma 2011), and atmospheric circulation patterns (Abatzoglu 2011). Kapnick and Hall (2012) find evidence that temperature increases have induced snowpack decline across 12 western US states and Canada during the mid to late portion of the

[11] Snowpack is defined as the accumulation of snow on the ground (Garfin et al. 2013).

[12] Snow water equivalent (SWE) is defined as the amount of water that would be obtained if the snowpack melted (Garfin et al. 2013).

snow season (i.e., March through May). Snowpack declines are due both to decreases in snow accumulation and increases in snowmelt, though some high-elevation regions in California and the southern Rocky Mountains experienced increased snow accumulation in the early portion of the snow season. As temperatures rise above freezing, even these locations experience a decline in snowpack. Pederson et al. (2011) use tree-ring analysis to illustrate the anomalous decline in snowpack across the North American cordillera since the 1980s, and attribute this decline to springtime warming caused by a decadal-scale shift in Pacific climate in the mid-1970s through mid-1980s. Minder (2010) uses physically based models (snowfall and snowmelt models) to study the changes in climatological snow accumulation due to local changes in temperature in the Cascade Mountains. They find that in the Cascades (and likely other moderate-elevation ranges), once warming exceeds a threshold, precipitation increases cannot compensate for loss in accumulation area. This suggests that mountain height may determine the extent to which temperature-induced precipitation could compensate for temperature-induced melting. Mote et al. (2005) use the Variable Infiltration Capacity hydrologic model with observed daily temperature and precipitation data to study changes in snow water equivalent (SWE) in the western United States. They find that the Cascade Mountains and, generally, mountains in Northern California have the greatest sensitivity, compared to other ranges in western North America, to temperature increases, particularly in the spring. Using linear regression, Svoma (2011) finds that total precipitation was the most statistically significant variable[13] related to spring snowpack density in the western United States. In addition to temperature and precipitation, Abatzoglu (2011) found that the intra-monthly variations of the Pacific-North American (PNA) atmospheric circulation pattern impacts the percent of falling as snow as well as snowmelt during winter. Abatzoglu (2011) suggests that the influence of the PNA has exacerbated the anthropogenic increase in the elevation of the freezing level. His work corroborates earlier findings of the influence of atmospheric circulation in winter season warming and early snowmelt in the Sierra Nevada Mountains (Abatzoglu 2011; Dettinger and Cayan 1995). Pierce et al. (2008) attribute the declining western United States snowpack over the latter half of the twentieth century to anthropogenic increases in greenhouse gases. They find that the ratio of snow water equivalent to water-year-to-date precipitation is declining through this period is much greater than could be explained by natural variability alone; suggesting that SWE is declining even as total precipitation is increasing. Loss in SWE is projected to increase as warming continues into the future (Pederson et al. 2011; Cayan et al. 2006). Even the low emissions (B1) scenario yields SWE losses in the San Joaquin, Sacramento and Trinity basin systems in the future as compared to the baseline period across both GCMs in the Cayan et al. (2006) study.

8. Sea level rise

The IPCC 5th Assessment Report (AR5) indicates that it is very likely that the rate of global mean sea level rise during the twenty-first century will exceed the rate observed during 1971-2010 (Church et al. 2013). The magnitude of sea level rise is higher in AR5 than AR4 due to improvements in land-ice modeling over the previous six years. Part of the increase in sea level rise is due to the increased mass of water in the oceans from melting ice and snowpack (Jevrejeva, Moore and Ginsted 2008). Along the California coast, mean sea level has risen roughly 2.2 cm per decade over the past 150 years (Hanak et al. 2011). The Sacramento-San

[13] Other variables in the study were: average air temperature (on days with no snowfall), average snowfall density, and fraction of precipitation falling as snow.

Joaquin Delta and San Francisco Bay are particularly vulnerable to sea level rise, as water flows in this region are partly driven by sea level (Hanak et al. 2011). Rises in sea level threaten to shift salinity landward, and ultimately to increase the salinity level in the San Francisco Bay Delta. Sea level rise will also exacerbate saltwater intrusion in coastal aquifers, thus creating salinity problems for irrigated agriculture.

9. Runoff/streamflow

April through July is peak runoff season in the western United States, and therefore, a critical period to study.[14] Observational studies have found there is a shift in peak spring flow timing, with increased peak flows in March and April, and decreases in May and June (Regonda et al. 2005); and, since the 1970s, the percentage of annual discharge from spring snowmelt has diminished (Cayan et al. 2001; Dettinger and Cayan 1995). This has led to the conclusion that spring is starting earlier in the western United States (Regonda et al. 2005; Cayan et al. 2001). Cayan et al. (2001) assert that anomalous spring temperatures are the biggest cause of observed earlier pulse timings. Das et al. (2011) suggest there may be a "seasonal asymmetry" in the response of streamflow to warming. Their results indicate that warm season (April-September) warming may be a key driver of annual streamflow changes in the Colorado, Columbia, and Southern Sierra basins, to a greater extent than cool season warming (October-March). They hypothesize that summer warming stimulates greater evapotranspiration and diminished soil moisture without a compensating process during the following winter to generate a streamflow increase.

The relationship between snow dynamics and runoff was also studied (Miller et al. 2011; Rauscher et al. 2008; Barnett et al. 2005; Stewart et al. 2005; Cayan et al. 2001). Stewart et al. (2005) suggest that snowmelt-driven runoff is the most predictable and reliable water resource in the western United States. Studying the Colorado River Basin, Miller et al. (2011) find that the timing of the last day snowpack season corresponds well to the volume of runoff observed during peak flow season. Rauscher et al. (2008) find that snowmelt-driven runoff may be caused by increases in winter temperatures in the western US. Further, assuming a projected temperature increase of 3-5°C (Christensen and Lettenmaier 2007), Rauscher et al. (2008) find that snowmelt-driven runoff may occur up to two months earlier.

10. Agronomic and economic models for projecting impact on crop yield

The previous section has identified climate impacts to water availability, a critical concern (politically and economically) for water-stressed areas such as the Southwest. An additional concern is the direct impact of climatic changes to crop yield, and ultimately agricultural profitability. This section begins with a general discussion of how climate variables impact crops. It is followed by a discussion of crop simulation models, particularly how climatic changes have been incorporated into crop simulation. Economic models and integrated assessments are subsequently discussed. The section ends with a summary of impacts to the southwestern United States, particularly California.

[14] Runoff occurs when excess water flows over the land as a result of the soil being fully infiltrated by precipitation or snowmelt (Wikipedia surface runoff page), whereas streamflow is the flow of water in streams, rivers and other channels (Wikipedia streamflow page).

Changes in climate variables, such as precipitation, temperature, CO_2, and solar radiation impact crop growth in complex ways. These responses depend upon the crop, local geography, and management practices. As discussed in the previous section, both temperature and precipitation impact the water cycle, leading to outcomes such as increases in precipitation extremes, drought, altered timing of streamflow, and earlier snowmelt. These will all impact water delivery to crops, and ultimately crop development and yield. Temperature also directly affects crop development. The literature suggests that moderate warming may increase yield in temperate regions, and decrease yield in semi-arid and tropical regions (Tubiello et al. 2007)[15]. There is a base temperature interval at which crop growth is initiated, and a maximum temperature interval at which crop growth ceases. There is also an optimum temperature interval at which crop growth is fastest (Walthall et al. 2012). Crops also exhibit a CO_2 fertilization effect. Increased atmospheric carbon dioxide stimulates photosynthesis, leading to increased plant productivity and decreased water use. However, the extent to which CO_2 dampens the effects of climate change remains unclear. Warmer temperatures also lead to increased evapotranspiration. Also, increases in water vapor could lead to increased cloud cover, and therefore a decrease in solar radiation. Overall, extreme temperature and periods of drought may have the most negative impact on crop growth and yield in the short run (Wheeler et al. 2000).

11. Crop models

Crop simulation models use mathematical relationships to predict the yield dynamics and growth rate for crops. Factors affecting crop growth are extremely complex, and these models help to isolate and study the most critical variables (e.g., soil nutrients, ambient temperature, soil moisture, etc.). Outputs from these models advance scientific understanding of domesticated plant growth, and provide practical information for agricultural extension specialists and farmers (e.g., regional suitability and potential productivity). Crop simulation models have also been employed as tools in agricultural management, such as comparing alternative management scenarios and testing different crop practices to soil quality (Iglesias et al. 2011; Hoogenboom 2000). While earlier models use weather data to simulate the effects of the local environments in which they were evaluated, more recent models systematically analyze climatic change impacts on general crop productivity (Hoogenboom 2000). Many studies use the output from various GCMs for input into the crop model.

Earlier studies found that global climate projections were too coarse to be incorporated into a local or regional crop simulation model. The majority of current studies use some form of downscaling to report on regional impacts, as opposed to earlier studies that used global-scale climate output. Statistical and dynamical downscaling of the GCM is employed to create more accurate regional yield estimates. Statistical downscaling employs a statistically based model to determine a relationship between local-scale climate variables and global-scale climate variables (Green et al. 2011). Dynamical downscaling refers to nesting a high-resolution regional climate model within a coarser global climate model to derive smaller-scale information. Studies have found disparities in yield projected from coarse and downscaled GCM output. For example, Carbone et al. (2003) examine the potential impacts of climate change on soybean and sorghum yield in the Southeast using two climate change scenarios with different spatial resolutions. The coarse scenario is produced from GCM output (i.e., CSIRO), while the fine-scale scenario is produced via dynamical downscaling. For soybean yield, authors found that the fine-scale model

[15] This does not take extreme events or CO_2 fertilization into account.

predicted a greater yield decline on average. Related to yield disparity, studies have also found disparities in economic benefits between GCM scales. For example, Adams, McCarl, and Mearns (2003) study the influence of GCM spatial scale on estimating climate impacts to both rainfed and irrigated agriculture in the United States, while holding the spatial scale of economic and crop models constant. They find that a finer scale in the climate model leads to reduced benefits or greater damages relative to a coarser scale.

11.1 Types of crop models

Broadly speaking, there are two types of crop models: (1) process-based and (2) production function models. Process-based models simulate physiological development, growth and yield of a crop on the basis of interaction between environmental variables (e.g., soil, climate) and plant physiological processes (e.g., photosynthesis, respiration, transpiration). These models calculate a causal relationship between environmental variables and physiological processes. Process-based crop models generally consist of at least three modules: (1) soil; (2) plant; and (3) atmospheric modules (Iglesias et al. 2011). Production function models relate seasonal crop yields to climatic variables using statistical methods such as regression, i.e., these models examine a correlative relationship of yields with climate (Carter and Saarikko 1996). The primary sources of data in these models are historical variations in weather and crop harvests. While these models predate process-based models and are considered simpler (Yin 2013; Hoogenboom 2000), they have become increasingly more sophisticated. There is general consensus that process-based models remain the gold standard. Table 1 lists some of the most commonly used crop and water balance models.

Production function models are contrasted with process-based models, because the former estimates the relationship between weather and crop yield; whereas, the latter estimates the relationship between weather and all phases of crop growth (Yin 2013). Process-based models allow the analyst to study a range of weather possibilities, even those that lie outside of the historical record (Adams, Wu and Houston 2006). Production function models cannot carry out analysis outside of the historical record, and thus impacts of future anomalous events cannot be assessed. The historical record becomes a poor predictor for future climate by the mid twenty-first century, when studies across different climate models have shown that predictions from low and high emissions scenarios significantly diverge. However, relying on the historical record can also be advantageous in production function modeling, particularly for a near-term (i.e., 20-30 years) projection. Production function models could capture effects of poorly understood socioeconomic and biophysical processes, such as the *actual* adaptations farmers have made to cropping systems (Adams, Wu, and Houston 2006) and pest dynamics (Lobell, Cahill, and Field 2007). Process-based models also have the capacity to take future CO_2 fertilization into account, whereas production function models cannot (Adams, Wu and Houston 2006; Carbone et al. 2003). For example, process-based models such as CROPGRO and CERES account for CO_2 fertilization by adjusting leaf stomatal resistance (Carbone et al. 2003). Though process-based models arguably provide the most accurate simulation of crop biophysical systems, these are highly data intensive. Therefore, only the essential staple crops (i.e., wheat, rice, maize, and soybean) have been extensively modeled. While these account for 85 percent of world cereal exports (Parry et al. 2004), these are all annual crops. Perennial crops have not been extensively modeled with process-based simulation, because they require several additional climatic and physiological variables due to their longer life (Lobell and Field 2011).

Comparing yield from various studies is neither a straightforward nor particularly meaningful exercise, as there is no standard method on how to classify, let alone interpret, the results from different crop models (White et al. 2011). And, since few regions are studied by more than one research group, the option of comparison is not even available. Focusing instead on methodologies is more constructive. This section is thus concerned with how crop simulation models have incorporated climatic change. As such, three main methodological improvements to both process-based and production function models is subsequently discussed: (1) agroclimatic zones (2) climate variability (3) CO_2 fertilization. To address the high level of regional specificity associated with yield projections, regional studies focusing on a smaller geographic area have been conducted (Carbone et al. 2003; Adams, McCarl, and Mearns 2003; Lobell and Field 2011). Other studies have first identified agro-climatic regions using a statistical clustering method, and then ascertained yield via crop simulation (Barnwal and Kotani 2013; Adams, Wu, and Houston 2006; Iglesias et al. 2000; Carter and Saarikko 1996). Some studies have incorporated CO_2 fertilization effects on crop yield (Stöckle et al. 2010; Carbone et al. 2003; Olesen et al. 2000). Others have introduced climate variability (e.g., number of extreme events) into yield analysis (Osbourne and Wheeler 2013; Olesen et al. 2000; Semenov et al. 1996; Semenov and Porter 1995).

11.2 Agroclimatic zones models

The aims of downscaling and agroclimatic mapping are overlapping, as both aim to study the spatial characteristics of climate. An agroclimatic region is defined as a zone with a characteristically unique interrelationship between a farming system and climate (Holden and Brereton 2004; White et al. 2011). Regions of optimal crop growth are partially dependent upon climate, and as climate shifts, so, too, do these regions of optimal growth. Carter and Saarikko (1996) couple a process-based crop model with agroclimatic indices and GIS to predict wheat yield in Finland. They capture the shift in regional suitability as a result of a 0.3°C per decade increase relative to their baseline of 1961-1990, finding that the suitability for wheat shifts northward roughly 35km per decade (not taking into account the institutional/socioeconomic feasibility of this shift). Holden and Brereton (2004) suggest that coupling crop simulation with agroclimatic zone identification could facilitate country-level analysis, since fewer agricultural plots would need to be evaluated. Instead, agricultural plots could be evaluated in terms of their regional representativeness. They use a statistical clustering technique to derive agroclimatic zones in Ireland for grass, barley, maize, potato, and soybean. The climate data (precipitation, temperature, solar radiation) is organized in 10x10 km grid squares, with the process-based crop simulation models run on each grid square. In a similar analysis, Iglesias et al. (2000) study the spatial implications of climate change on wheat production in Spain by using a statistical approach to identify agroclimatic zones in Spain. These zones are based on spatial climatic and CERES-wheat crop data. Across all zones, they find that wheat yield is responsive to irrigation water, precipitation, and temperature, but not CO_2 concentration. Barnwal and Kotani (2013) study the relationship between climate variables (i.e., average temperature and total precipitation) in agroclimatic zones and rice yield in India. They find that direction of climate impact varies according to agroclimatic zone.

12. CO_2 fertilization

Increased atmospheric carbon dioxide stimulates photosynthesis, leading to increased plant productivity and decreased water and nutrient use (Tubiello, Soussana, and Howden 2007). Free air carbon dioxide enrichment (FACE) experiments are needed to validate simulated effects of

CO_2 increases in the field. Theory suggests that benefits from elevated CO_2 concentrations will depend upon plant type and irrigation. C3 photosynthetic plants (e.g., wheat, potatoes, soybeans) will benefit more than C4 plants (e.g., corn, sorghum) (Stockle et al. 2010), and rainfed cropping systems will benefit more than irrigated systems (Easterling et al. 2007). However, the extent to which CO_2 fertilization mitigates climate-induced water scarcity in the field still lacks scientific consensus. One related debate is on the consistency between simulated CO_2 effects and FACE experiments, with some suggesting that the former overestimate the CO_2 effect (Long et al. 2006) and others suggesting that the former reproduces the latter (Tubiello et al. 2007). Improving simulations of leaf area dynamics and understanding complex factors (e.g., pests, weeds, nutrients, soil water, etc.) will ultimately lead to more accurate modeling (Challinor et al. 2009, Tubiello, Soussana, and Howden 2007).

Stöckle et al. (2010) study the impact of climate change (CO_2, temperature, precipitation, evapotranspiration) on eastern Washington state agriculture (wheat, apples, potatoes) using the CropSyst simulation model coupled with four GCMs. Elevated CO_2 increases winter wheat yield at all study locations, while only stabilizing or having minimal effect on yields for the other crops. Also studying winter wheat, Olesen et al. (2000) find CO_2 effects in Denmark to be constant across the three soils types they evaluate (i.e., fine, loamy, sandy) for all precipitation levels and duration of dry spells. Carbone et al. (2003) model the impact of CO_2 fertilization on soybean and sorghum yield in the Southeast. They find that accounting for CO_2 fertilization mitigates the yield decline related to climate change without CO_2 fertilization (e.g., from 69 to 54 percent for the soybean RCM; and from 51 to 42 percent for sorghum), but to a much lesser extent than the farmer adaptation strategies. With adaptation strategies (i.e., changing the planting date and crop mix), yield only decreases by 18 percent and 15 percent, respectively, for soybean and sorghum.

Lee, Gryze and Six (2011) tested climate projections with and without a CO_2 effect on seven field crops in the Central Valley of California. They included a CO_2 fertilization effect by assuming a CO_2 increase of 350 ppmv from 1990 levels enhanced net primary production by 10 percent for all crops except alfalfa and maize.[16] They found that by the end of the twenty-first century, CO_2 fertilization increased crop yields by 2 to 16 percent (above the model without CO_2 effects) under the high-emissions scenario. There was a much smaller yield increase (1-8 percent) under the low-emissions scenario. Adams, Wu, and Houston (2006) account for increased water use efficiency via increased atmospheric CO_2 concentration. They develop evapotranspiration functions that estimate crop water use in California. Their results support the hypothesis that CO_2 fertilization increased yield in cooler regions in which climate change stimulates crop growth (e.g., mountain and coastal areas), and mitigates the declines yields in which climate change will decrease crop yield (e.g., San Joaquin Valley). However, higher concentrations of CO_2 and larger magnitudes of climate change dampen the positive effects of CO_2 fertilization on yield.

13. Climate and yield variability

Climate variability is an important concern for farmers, since it affects critical management decisions, such as planting dates and, even, crop choice. It can be defined as changes in daily precipitation intensity, duration of wet and dry spells, and mean and variance of temperature (Olesen et al. 2000; Semenov et al. 1996). Climate variability (more so than mean climate) is

[16] They also assume a C:N ration for biomass by 25 percent, and decreased transpiration rate by 23 percent.

linked to extreme events (Katz and Brown 1992), which, in turn, contribute most to short-run crop loss (Wheeler et al. 2000).[17] This relationship is relatively stronger as the extreme event increases in intensity (Katz and Brown 1992). Climate variability may also affect yield *variability,* although the direction of the influence is highly dependent on crop, region, and climate variable (i.e., temperature or precipitation).

Most studies examine the effect of climate variability on absolute yield. Semenov and Porter (1995) find that climate variability can have significant effects on crop yield. Semenov et al. (1996) assess model predictions on crop yield with climate variability in Spain and the United Kingdom. They find substantial differences in predicted yield between mean climate and climate variability for some regions in Seville (Spain) and Rothamsted (UK). For example, in Seville, under mean changes, yield increased by a modest amount, but decreased under climate variability. Olesen et al. (2000) model the sensitivity of grain yield to changes in mean temperature, temperature variability, precipitation, length of dry spells, and CO_2 concentration for four soil types in Denmark. They find a very small response to changes in temperature variability. However, in sandy soils, dry spells and precipitation exhibit a relatively strong influence on yield. Jackson et al. (2011) use the process-based model, DAYCENT, to examine how heat waves affect six crops (alfalfa, maize, rice, sunflower, tomato, and wheat) in Yolo County, California. They find that heat waves in May negatively affect all crop yields except alfalfa and wheat; whereas, heat waves in June have a negative effect on only maize and sunflower. Repeated heat waves during May through July have an even more pronounced effect on yields for all crops except alfalfa and wheat.

Some studies specifically focus on the relationship between climate and yield variability (Osbourne and Wheeler 2013; Chen et al. 2004). Osbourne and Wheeler (2013) jointly examine yield and climate variability for global production of rice, wheat, and maize over the past 50 years. For several crop-country combinations, they find that an increase in climate variability actually decreases yield variability. Chen et al. (2004) use panel data on U.S. corn, cotton, sorghum and wheat yields to determine a statistical relationship between yield and climate conditions. They find that increased rainfall decreases variability in yield for corn and cotton, but increase the variability for sorghum. Higher temperatures decrease the variability in yield for cotton and sorghum, but increase it for corn. The results for wheat were not as clear.

14. Economic optimization and simulation models

Various economic assessment tools have been employed to incorporate farmer behavior into a broader study of climate impacts on agriculture. Mathematical programming models couple the crop simulation models discussed previously with farm and economy-wide responses. Econometric models use regression-based approaches to calculate agricultural land value or net revenue. These models do not directly incorporate crop yield. In practice, many models have both programming and econometric features (Adams 1999). For example, mathematical (optimization) programming models often use econometric techniques to estimate parameters (Connor et al. 2009; Adams 1999). Both approaches model the farmer as a profit maximizing agent who has historically taken climate signals into account to adjust farming practices to yield the maximum benefit. The extent to which s/he will take future climate projections into account depends on key assumptions in each model.

[17] Katz and Brown (1992) refer generally to the mean and variability as the location and scale parameters, respectively. Under a normal distribution, these would be the mean and standard deviation parameters, respectively.

14.1 Mathematical programming models

The major advantage of mathematical programming models is that they can characterize a broader range of adaptations and costs, beyond that reflected in the historical record (Connor et al. 2009). Some of these models can also incorporate CO_2 fertilization effects (Adams et al. 1999). These models tend to require a high degree of computing power/complexity as they are more data intensive than econometric models. Many of the earlier programming studies are global scale, and often study the spatial implications of climate change on world food production (Fischer et al. 2005; Parry et al. 2004). Adams et al. (1995) specifically model the United States agricultural sector. Some studies focus on particular water sources (Connor et al. 2009; Mejias et al. 2004; Chen, Gillig and McCarl 2001). A few studies have focused on the Southwest (Howitt and Pienaar 2006; Medellin-Azuara et al. 2011; Frisvold and Konyar 2012), although these primarily emanate from a single research group.

Several global-level programming models have been developed to study the climate impacts on agricultural land area and global food trade (Parry et al. 2004, Fischer et al. 2005, Sands and Edmonds 2005). Parry et al. (2004) present a global model for evaluating the impacts of climate change on crop yield for wheat, rice, maize, and soybean. Yield transfer functions incorporate: (a) crop responses to changes in temperature and precipitation with current management, (b) crop responses to temperature and precipitation with farm-level and regional adjustments, and (c) crop responses to carbon dioxide. The yield results are input into the Basic Linked System (BLS) global food trade model. Incorporating potential adaptation scenarios, the authors find that on a global scale, the IPCC scenarios result in yield decreases in developing countries and yield increases in developed countries. Fischer et al. (2005) also use the BLS model to study climate impacts on global cereal production. They assess the impacts of climate change on crop yield using the FAO/IIASA agro-ecological zone model (AEZ), and calculate changes to the potential crop production area. The results of that part of the model are used as an input into the BLS model, which assesses alternative development pathways as well as key trends in food demand, production projected, and trade for the twenty-first century. Sands and Edmonds (2005) conduct an integrated global (i.e., 14 world regions) assessment using a reduced-form representation of agriculture and forestry linked to a model of the world energy system. Their objective is to study climate impacts (with and without CO_2 fertilization) on land use, land prices, and economic welfare. They use process-based crop simulation models to drive their economic model. The Agriculture and Land Use model allocates land among crops, pasture, and forests according to the economic return from each land use type in each region. Each landowner selects the land use with the greatest economic return, and a reduced-form solution can be obtained for the share of total land in each region allocated to each land use as a function of prices and non-land costs of production. They find that CO_2 fertilization is a key determinant of changes in yield and economic welfare in the United States.

Adams et al. (1995) present a spatial equilibrium model of the U.S. agricultural sector known as the Agricultural Sector Model (ASM). They use crop simulation models to derive the predicted changes in yields for wheat, corn, and soybeans, which is then combined with economic models of farm-level crop choice using linear or non-linear programming. Adams et al. (1999) extend the ASM model to allow dynamic projection of crop yields, domestic demand and exports for major commodities. Adams, McCarl and Mearns (2003) use an updated version of their ASM model to study the influence of GCM spatial scale on estimating climate impacts to both rainfed and irrigated agriculture in the United States. The updated ASM includes price, production and regional impacts under stochastic crop yield outcomes. A regional climate model (i.e., RegCM) is nested within a GCM (i.e., CSIRO) and run for three U.S. sub-regions (i.e., western, Great Lakes, and southeastern regions). They find that a finer scale in the climate model leads to reduced benefits or greater damages, relative to a coarser scale.

Chen, Gillig, and McCarl (2001) assess the economic impacts of climate change on the region surrounding the Edwards Aquifer using an economic and water balance model called EDSIM. EDSIM is a two-stage stochastic programming model that simulates regional municipal, industrial and agricultural water use, irrigated versus dryland production and choice of irrigation delivery system (Chen, Gillig, and McCarl 2001). Crop yield estimates are taken from the EPIC process-based model. Regional welfare is computed the sum of net farm income and (municipal and industrial) consumer's surplus. As mentioned earlier in this review, increasing temperatures reduce groundwater recharge, requiring farmers to pump deeper into the aquifer. This increases pumping costs, and ultimately results in a 1 to 2 percent reduction in regional irrigated agricultural profits.

Mejías et al. (2004) study the impacts of climate change on water pricing policies for irrigated agriculture in Spain. Using a stochastic programming model, they estimate farmers' response to the application of water pricing policies in different agricultural policy scenarios. Water availability is driven by different climate change scenarios. Their results suggest that farmers are generally responsive to prices; however, there is an inelastic demand for water during drought years in spite of higher water prices.

Connor et al. (2009) model irrigated agriculture in the Lower Murray Darling Basin using a two-stage stochastic model that simultaneously estimates long- and short-run adjustments. In the first stage, the farmer selects long-run fixed capital investments and, in the second stage, the farmer makes short-run decisions regarding water application rates and acreage fallowed. The second stage decisions are conditional on the first stage decisions. The study uses a water balance model to predict water availability under three different climate scenarios. Connor et al. (2009) model crop yield based on a function that is quadratic in water availability. They find that yield reductions and high water costs (caused by increased temperature and low allocation) lead to a large decline in profits.

Howitt and Pienaar (2006) use an integrated approach to analyze impacts of climate change on irrigated agriculture in California. The Statewide Agricultural Production Model (SWAP) identifies region-specific water demand and the value of agricultural output. By comparing climate change scenarios with baseline conditions, Howitt and Pienaar (2006) measure the welfare impacts of global warming. Under the warm and wet scenario (HadCM2), there is only a small increase in net farm income even though runoff has increased. The cool and dry scenario (PCM) results in a 24 percent cut in water supply and 14 percent reduction in farmland across California. However, net revenues only fall by roughly 6 percent under the PCM scenario. These results suggest that agriculture will move away from low-value crops under future climate-induced water shortages. Medellin-Azuara et al. (2011) extend the analysis of Howitt's SWAP model using a different GCM (GFDL), which Cayan et al. (2008) suggest is the most consistent with historic climate observations in California. Medellin-Azuara et al. (2011) find that acreage decreases for low-value agriculture (e.g., pasture, field, and grain crops). Irrigated pasture declines by over 90 percent in Sacramento, San Joaquin, and Southern California by 2050. They also find that the Sacramento and San Joaquin regions exhibit the largest decline in low-value crops.

14.2 Computable General Equilibrium (CGE) models

CGE models are a special class of mathematical programming models. Whereas other economic models are based on a partial equilibrium of the agricultural sector, CGE models allow scarce resources to move between sectors of the economy in response to economic incentives. Indeed climate change impacts have the potential to affect the entire economy and alter both input and output prices (Mendelsohn and Dinar 2009). CGE models have the additional advantage of accounting for inter-sectoral foreign trade. However, these models have a high margin of error as data from different sources and sectors is aggregated. These are also the most data-intensive of the economic modeling approaches (Schlenker, Hanneman, and Fisher 2006).

Sherony et al. (1991) quantify the economic impacts of permanent crop loss from drought in the US using a CGE model linked to a crop simulation model (i.e., EPIC). They find that retail food prices and overall price level will be minimally impacted by the crop loss from short-term drought partly because international trade balances will adjust to mitigate the domestic price impact.[18] They conclude that agricultural policies that promote price flexibility, while protecting individual farmers as the industry adapts to environmental changes, will minimize the effect of crop loss on the overall economy.

In addition to accounting for foreign trade, many CGE studies are international in scope (Darwin 1999; Winters et al. 1998). Darwin (1999) developed the Future Agricultural Resources Model (FARM), which uses a geographic information system to empirically link climatically derived land classes with other inputs and agricultural outputs in a global CGE model. The model divides the world into eight geographic regions, each with 11 economic sectors that produce 13 tradable commodities. One welfare measure tracked by the model is equilibrium income from agricultural land (e.g., lower incomes mean that agricultural landowners have less money to spend on consumer goods and services). Winters et al. (1998) focus on climate impacts on cereal importing nations in Africa, Asia, and Latin America. Two direct effects on agriculture are anticipated: (1) reduction in overall crop yields that will depend on individual crop productivity changes (as predicted by climate and crop models), as well as composition of agriculture in the country, and (2) impact on global supply and demand and therefore world agricultural commodity prices. Their model captures structural changes in the economy. They find that agricultural production will fall in all countries studied for both cereal and export crops. As incomes fall, there will be a global shrinkage of trade, which will have negative repercussions worldwide. Africa will suffer the greatest income loss and drop in consumption of low-income households due to low substitution possibilities between imported and domestic cereals. More recently, Arndt et al. (2012) estimate the impact of climate change on food security in Tanzania by employing a dynamic CGE model and process-based crop model (i.e., CLICROP). They find that domestic agricultural production is likely to decline due to climate change. This, in turn, has strong implications for food security in the country by 2050.

Frisvold and Konyar (2012) employ a partial equilibrium analysis using the U.S. Agricultural Resources Model (USARM) to study the impacts of climate-induced water scarcity for agriculture in the Southwest. USARM is a nonlinear programming model that defines cropping activities by a nested constant elasticity of substitution production function. The model endogenously determines the quantities of inputs used in each activity. They simulate a 25

[18] Sherony et al. (1991) find that overall price will also be minimally impacted because farm gate prices are only a small fraction of food retail prices, which are themselves only a small fraction of the Consumer Price Index.

percent reduction in water use[19], and find that including adaptations (i.e., shifting between irrigated and rainfed production, altering water use on irrigated acreage, altering use of inputs on planted acres, fallowing land, and changing the crop mix) reduces the cost of water shortages to producers by 66 percent as compared to a simulation with fallowing alone.

15. Econometric models

15.1 Ricardian models

Econometric methods do not directly take crop yield into account, thus these are not linked to crop simulation models. The Ricardian method econometrically estimates the impact of climate change on the value of farm real estate (Mendelsohn, Nordhause, and Shaw, 1994; Mendelsohn and Dinar 2009; Darwin 1999). It does so by regressing land value or net revenue on a set of climate variables, environmental characteristics, exogenous market factors, and other control variables[20] (Mendelsohn and Dinar 2009). Thus the estimated climate parameter in the regression model represents the economic value of long-term climatic changes on agriculture. It is expected that regions with more abundant and secure access to water will result in higher farmland values (Schlenker et al. 2007). Structural Ricardian models modify the traditional model by adopting a two-stage estimation procedure. In the first stage, the farmer chooses farm type, irrigation technology, and crop species. The conditional net revenue for each choice is then modeled in the second stage (Mendelsohn and Dinar 2009). These models capture adaptation decisions by farmers and will also be discussed in the Adaptation Section of this review. With the Ricardian approach, all farmer adaptations are accounted for because structural changes and farmer responses are implicit in the analysis (Adams et al. 1998). The approach allows one to calculate the direct impact of each farmer, county, or state in contrast to a highly aggregated approach, such as CGE (Schlenker, Hanneman, and Fisher 2006). Some of the disadvantages of the original Ricardian model (i.e., Mendelsohn, Nordhaus and Shaw 1994) have been corrected in more recent studies. For example, the original study aggregated rainfed and irrigation water. This overstates the importance of the precipitation variable in irrigated areas, where the relationship on yield increase and precipitation is much weaker than in rainfed areas. Schlenker et al. (2005, 2006) address irrigation separately. Another critique of the Ricardian approach is that it assumes prices and technology will remain constant (Connor et al. 2009; Deschenes and Greenstone 2007; Schlenker et al. 2005). It can reasonably be argued that the impact of prices and technology in the long-run projections associated with climate impact studies are small (Mendelsohn and Dinar 2009). What is more uncertain is future water supply costs in irrigated areas, which are likely to surpass current levels of relatively secure supply (Schlenker et al. 2005). Connor et al. (2009) also argue that different types of crops (e.g., perennial, annual, etc.) should not be aggregated in Ricardian studies. A final criticism is that Ricardian models do not take CO_2 fertilization into account (Deschenes and Greenstone 2007). This is a criticism of all statistical approaches, including the production function approach in crop simulation. Other econometric approaches have similar criticisms to the Ricardian approach. One specific criticism of the year-by-year analysis of Deschenes and Greenstone (2007) is that it cannot account for long-run farmer adaptations.

[19] Frisvold and Konyar (2012) simulate a 25 percent reduction in Arizona, Colorado, Nevada, New Mexico, and Utah. They simulate a 5 percent reduction in California. The results presented are only for the five states with a 25 percent reduction since the results for California were negligible.

[20] Farm choices such as labor, capital, and crop choice are considered endogenous variables and are not included in the regression (Mendelsohn and Dinar 2009).

Mendelson, Nordhaus, and Shaw (1994) is the classic paper, using a Ricardian model, in which land values are regressed on climate, soil and socioeconomic variables in order to estimate the best value function across 2,933 U.S. counties. Their underlying hypothesis is that farmers have historically taken climate into account, and adjusted inputs and outputs accordingly. Their key assumption is that the economy has adjusted completely to the given climate, therefore, land prices reflect the long-run equilibrium value. They use the 30-year average of daily mean temperature and monthly precipitation for January, April, July, and October in their analysis. Under a scenario of CO_2 doubling, they find that farmland values actually increase by $20-35 billion by 2050. However, subsequent studies (Schlenker et al. 2006; Schlenker et al. 2005; Mendelsohn and Dinar 2003) illustrate that aggregating rainfed and irrigated agriculture into a single analysis biases the climate estimators. They challenge assumptions in Mendelsohn, Nordhaus, and Shaw (1994) regarding source and cost of water supply, arguing that precipitation is not an appropriate source of agricultural water in irrigated areas. Irrigation exists in these areas because there is a shortage of precipitation to begin with. Schlenker et al. (2006; 2005) also argue that supply costs of water will increase in irrigated areas beyond the current level although the Mendelsohn, Nordhaus, and Shaw (1994) model does not account for these changes. In addition, Schlenker et al. (2006) find that counties on opposite sides of the 100^{th} meridian line (divides rainfed from irrigated agriculture in the United States) are statistically different at the 5 percent level for average precipitation between April and September. This confirms that precipitation factors differently in Ricardian equations of rainfed and irrigated agriculture.

Subsequent studies examine the effect of access to surface water on the ability to adapt. Mendelsohn and Dinar (2003) assess the extent to which surface water withdrawal explains the variation of U.S. farmland values. They also test whether adding these variables to the original Ricardian model (Mendelsohn, Nordhaus, and Shaw 1994) affects the climate sensitivity of agriculture. They find that including a surface water variable increases the value of U.S. farmland to an extent, but this value declines as water supply increases. They also find that the effect of surface water on climate sensitivity is positive, but small. Schlenker et al. (2007) study farms in 112 irrigation districts across California, accounting for slightly more than half of the irrigated area in the state. In addition to using a precipitation variable in the model, Schlenker et al. (2007) include two statistics that measure access to irrigation water: (1) average surface water deliveries per acre in each district over the period 1992-2002; and (2) groundwater use based on data from more than 15,000 wells in the Central Valley. They find that the surface water statistic is statistically significant, suggesting that temperature impacts on surface water affect farmland value. However, their groundwater statistic is not statistically significant.

Some studies present a different measure of the climate variable known as degree days, which are the sum of degrees above a lower baseline and below an upper threshold during the growing season (Schlenker and Roberts 2009; Deschenes and Greenstone 2007; Schlenker et al. 2006). Seo et al. (2009) find that climate variables (i.e., precipitation and temperature) are statistically significant in determining farm net revenue across different agro-ecological zones in eleven African countries. The data suggest that farmers in different agro-ecological zones, as defined by the Food and Agricultural Organization, employ different farming practices (e.g., crop choice, livestock choice, etc.). Furthermore, the effects of climate change are found to be different across the continent. Currently productive areas (i.e., dry/moist savannah) are found to be more vulnerable to climate change, while currently less productive areas (i.e., humid forest or sub-humid areas) become more productive in the future. Additionally, the authors use the estimated coefficients to predict long-term climate impacts out to 2100. Using a “hot and dry”

(Canadian Climate Center) and "mild and wet" (Parallel Climate Model), Seo et al. find that the former results in net revenue losses, while the latter results in net revenue gains. Massetti and Mendelsohn (2011) extend Ricardian analysis to panel data, suggesting that the model may not be properly specified with cross-sectional data alone.

15.2 Other econometric models

Deschenes and Greenstone (2007) estimate the effects of random year-to-year fluctuations in temperature and precipitation on U.S. agricultural profits using yearly county and state fixed effects. One important way in which their approach differs from Ricardian approaches is that their dependent variable is county-level agricultural profits, whereas the Ricardian approach uses land value. Land values represent long-run characteristics of sites (e.g., climate) rather than annual realizations of a given variable (e.g., year-to-year weather). However, farm revenues can be affected by yearly weather realizations. They suggest that climate change will lead to a 4 percent increase in annual agricultural profits by the end of the twenty first century. However, this estimate is corrected in Deschenes and Greenstone (2012) after accounting for data errors in the original paper. They find that agricultural profits are reduced by the end of the twenty first century. Ultimately, this highlights the sensitivity of profit calculations to climate projections. Deschenes and Kolstad (2011) extend this approach to a county-level analysis of California using a GCM (i.e., CCSM3). They find that climate variables (i.e., degree days and total annual precipitation) negatively impact aggregate agricultural profits in California by the end of the twenty first century.

Blignaut et al. (2009) construct an econometric model to specifically analyze the effects of decreasing rainfall on agricultural profits in South Africa. Using a three-dimensional panel data set, Blignaut et al. (2009) develop a Seemingly Unrelated Regression model. They find that that each 1 percent decrease in precipitation leads to a concomitant 1.1 percent decrease in maize production, and 0.5 percent decrease in winter wheat production.

16. Modeling adaptation to climatic changes

It is important to take farm-level adaptation strategies into account when developing models of future farm production in the southwestern United States, particularly those adaptation strategies that will combat negative impacts on crop growth from rising temperatures and shifted timing of the growing season due to changing snowmelt and runoff dynamics. The IPCC defines adaptation as an adjustment of natural or human systems in response to actual or expected climatic stimuli in order to reduce harm or take advantage of opportunities (Bizikova et al. 2012). Many models evaluate the impacts of climate change on economic welfare (Arndt et al. 2012; Fischer et al. 2005; Gibbons and Ramsden 2005; Sands and Edmonds 2005; Parry et al. 2004; Adams, McCarl, and Mearns 2003). However, these do not incorporate the range of strategies that farmers could employ – e.g., crop mix, input (technology) mix, and timing of operations – to compensate for the negative climatic impacts, which tends to result in an overestimate of damages (Smit and Skinner 2002; Segerson and Dixon 1999). Although less common as a topic of economic research, mitigation technologies could compound the benefits to the agricultural industry. Any long-run strategy will incorporate farm-level emissions reductions *and* adaptations to climatic changes, perhaps even exploiting this synergistically (e.g., increased irrigation and fertilization necessary to maintain production in marginal semi-arid regions may enhance the ability of these soils to sequester carbon) (Jackson et al. 2012; Rosenzweig and Tubiello 2007).

17. Types of adaptation studies

The modeling methods used to capture farm-level adaptations are arguably as diverse as the research questions driving them. Some studies incorporate alternative adaptation policy scenarios by means of a decision-support system, which is a computer-based information system that supports institutional decision-making. The Water Evaluation and Planning (WEAP) decision support system is discussed in the context of being coupled with crop simulation and economic optimization. In other approaches, yield is less important than the factors influencing farmer behavior to adapt. Inherent in these other approaches is the assumption that best management practices are "best" insofar as proper incentives are in place for them to be adopted. Such approaches examine the extent or influences of technology adoption (i.e., Ricardian and trait-based approaches),[21] risk aversion behavior of farmers as it relates to adaptation practices, (Menapace, Colson, and Raffaelli 2012; Purvis et al. 1995) impact of social networks and social learning on technology adoption (Maertens and Barrett 2012; Conly and Udry 2010; Bandiera and Rasul 2006; Foster and Rosenzweig 1995).

17.1 Decision support system models

Decision support systems are computer-based information systems used by researchers, policy-makers, and farmers to make optimal crop management decisions. These are modular systems that link climate projection, crop simulation, and alternative management scenarios. An example of a simple modular decision support framework is presented in Figure 1, where GCM output is fed into process-based crop models (CERES), irrigation demand model (CROPWAT), and a water balance model (WATBAL). This information, in turn, is fed into a decision support system (WEAP) to conduct policy analysis[22]. Rosenzweig et al. (2004) evaluate the reliability of irrigation via changes in crop water demand and water availability for major maize and soybean growing areas in Argentina, Brazil, China, Hungary, Romania, and the United States. Specifically, they study the effect of three adaptations (efficient irrigation technology, changes in irrigated area, and alternative cultivars) on water availability to agriculture. WEAP is an optimization algorithm that balances water supply among different sectors. The results from the WEAP model suggest that, in the relatively water-abundant areas studied, increased water demands from population, industry, agriculture, and supply changes from climate change can be met as long as there are water efficiency and conservation measures in place. Blanco-Guiterrez et al. (2013) use the WEAP model for a smaller geographic scale to assess two policy interventions for a semi-arid region in the Guadiana Basin in Spain: (1) minimum environmental flow requirements, and (2) reduction in legal allocation of water supplied for irrigation[23]. Their results indicate that minimum environmental flow requirements may disproportionately affect rice farmers, who could experience up to a 40 percent decline in irrigation water, translating into a roughly 20 percent decline in income. Reduction in legal allocation of irrigation water under the Guadiana River Basin Management Plan causes a lower decline in irrigation water, but it may be insufficient to meet environmental flow requirements. Purkey et al. (2008) apply the WEAP model to study the impacts of adaptations (i.e., irrigation efficiency and shifting cropping

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[21] Technology adoption refers to use of a new technology, whereas, technological adaptation broadly refers to changing one's practices (e.g., adopting new technology, modifying existing technology, etc.) in response to climate change.

[22] Please note that the entire modeling framework is housed in DSSAT. The specific decision support system used is WEAP.

[23] Legal amount is determined by the Guadiana River Basin Management Plan.

patterns) to irrigated agriculture in California's Sacramento Valley. They find that the combined effect of improved irrigation technologies and shifting cropping patterns reduces future increases in water demand to their current level. Without such adaptations, water demand increases through the twenty-first century.

17.2 Classic adoption models

Standard/classic technology models are based upon bi- and multinomial reduced form comparison between profits (or utility) of distinct technology alternatives (Useche, Barham and Foltz 2012; Negri and Brooks 1990; Caswell and Zilberman 1986; Feder, Just and Zilberman 1985; Caswell and Zilberman 1985). In a classic paper, Caswell and Zilberman (1986) suggest that technology is used to augment the soil's water-holding capacity. Negri and Brooks (1990) support this finding. They present two discrete choice models to assess the probability of choosing between two water conservation technologies (i.e., sprinkler and tailwater recovery pits). Using a binomial logit model on national cross-sectional farm data, Negri and Brooks (1990) estimate technology-specific profit functions (which are each functions of input and output prices, a fixed land allocation, and exogenous physical properties).[24] The profit-maximizing farmer compares, and chooses the technology yielding the greatest profit. Ultimately, their results suggest that land quality (i.e., soil water-holding capacity) is a statistically significant determinant of technology choice. And, even in this early study, they find that climate is also a statistically significant determinant of technology choice. Caswell and Zilberman (1985) estimate the likelihood of using three different irrigation technologies (i.e., drip, sprinkler, and surface) in six California counties in the Central Valley. Under a multinomial logit framework, adoption probability is estimated using land shares of each respective irrigation technology within each county. One important result of their analysis is that local differences on adoption rates tend to be more significant when the technology is newer, and decrease as the technology becomes mature.

Although the original Ricardian models do not provide insight on how farmers are adapting to climate change (e.g., Mendelsohn, Nordhaus, and Shaw 1994), more contemporary Ricardian models (i.e., Structural Ricardian models) address adaptation by presenting irrigation technology as a choice (Mendelsohn and Seo 2007). Mendelsohn and Seo (2007) use a multinomial logit to model farm choice, followed by a binomial logit to model irrigation choice. The assumption is that each farmer will choose the combination of farm type and irrigation technology that maximizes expected net revenues. The difference between the future predicted land value under different climate change scenarios and current expected land value represents the welfare effect of climate change. Fleischer and Kurukulasuriya (2011) use a two-stage model: in the first stage, they model the choice of whether to adopt the technology or not, and in the second stage, they model the conditional income earned by different types of farmers. They find that farmers favor irrigation in warmer and drier African climates with good flow during the spring and fall. Using different climate change scenarios, they also find that irrigation technology is responsive to climatic changes. Wang et al. (2010) employ Ricardian methods to study crop choice among nine major crops in China. They use a multinomial logit model to study the impact of climatic variables (i.e., monthly temperature and precipitation) on the probability of choosing each crop. Wang et al. (2010) generally find that a marginal increase in temperature increases the probability of choosing maize and cotton, while a marginal increase in precipitation increases

[24] Their model assumes that all other inputs and outputs are optimized conditional on the technology choice.

the probability that farmers choose wheat. Fleischer, Mendelsohn and Dinar (2011) modify the Ricardian method to model how technological decisions may come as "bundles" of simultaneous rather than independent choices (e.g., crop choice, irrigation technology and cover are bundled as one choice). They apply this model to farms in Israel, and find that some bundles are particularly sensitive to annual mean temperature increase (i.e., many farmers will shift to fruits, irrigation and net cover). The lack of sensitivity to annual mean precipitation is expected, given that Israel receives very little precipitation to begin with.

Trait-based approaches model agricultural technologies as a collection of individual traits that affect farm household utility. These differ from earlier studies on technology choice because they focus on the attributes of a technology rather than attributes of the farm, or other inputs. While other technology choice models strive to address how farmers have adapted to temperature and precipitation changes, trait-based models are inherently behavioral as these strive to address why farmers have chosen their particular mix of technologies. The farmer's maximization problem is expressed as a choice of the crop variety that yields highest utility, which includes farmer knowledge of the traits of each agricultural technology, expected profitability of each technology, tastes for the traits, and farm characteristics (Useche, Barham and Foltz 2012). Useche, Barham and Foltz (2012) suggest that trait-based approaches are particularly useful when technology traits exhibit non-pecuniary effects or give rise to non-separability. Useche, Barham, and Foltz (2009) model the adoption of genetically modified corn for four different varieties (Ht, Bt, Ht/Bt, non-GM) using survey data from Minnesota and Wisconsin. They perform a multinomial logit demand analysis to derive shadow price estimates for these four seed traits. They are also able to account for farm-level heterogeneity in these estimates. Analogous to Fleischer, Mendelsohn, and Dinar (2011), trait-based models have used the underlying concept of bundles of technology. Foltz, Useche, and Barham (2012) test the differences in demand for crop yield protection via three technology options: (1) bundled warrantees, (2) drought-tolerance as a GM trait, and (3) drought-tolerance as a non-GM trait. They find that non-GM adopters are willing to pay more for drought-tolerance in a non-GM seed. Hedonic models also assess farmer demand for different crop and technology traits. Hedonic price analysis is employed to study the relationship between prices and attributes for banana farmers in three regions of Uganda (Edmeades 2007). The marginal implicit prices of crop attributes – quality, bunch size, and fruit size – are computed separately for each region. The implicit value of each attribute is a function of the marginal implicit prices and levels of other attributes in each region.

17.3 Risk-based approaches

Like trait-based modeling, methods that incorporate risk aversion focus on the influences affecting farmer choice (i.e., "why?") more than the concrete choices a farmer makes (i.e., "what?"). Purvis et al. (1995) invoke investment theory to model agricultural technology adoption in their classic paper on free-stall dairy housing for farms in Texas. Once the researchers account for uncertainty and assume complete irreversibility, the hurdle rate required for triggering technology adoption doubles. They also find that the discrepancy between expected returns from investing and expected benefits from delaying is greatest for farmers applying lower discount rates and when there is more uncertainty in an investment. Menapace, Colson, and Raffaelli (2012) find a positive correlation between risk aversion and subjective loss perception. They find that farmers who are more risk averse tend to hold a higher ex-ante perception of loss occurring due to weather events than farmers who are less risk averse. As such, excluding risk aversion will underestimate the costs of changing farming practices (De Pinto et al. 2013). De Pinto et al. (2013) run a simulation of small-holder farms in Ghana, and find that models that assume the farmer is risk neutral underestimate the cost of mitigation technologies, and thus may contribute to the low rate of mitigation technology adoption. This suggests that a range of risk attitudes need to be considered when developing simulation models on the cost of adaptation and mitigation technologies.

17.4 Social networks

Some researchers have explored the extent to which social networks affect farmers' learning about and adoption of agricultural technologies (Maertens and Barrett 2012; Conley and Udry 2010; Foster and Rosenzweig 2010; Bandiera and Rasul 2006; Cameron 1999; Foster and Rosenzweig 1995). A social network is an institution consisting of individual members (i.e., nodes) and the links among them through which information, money, or goods/services flow (Maertens and Barrett 2012). Cameron (1999) suggests that panel data provides the best evidence that learning – through doing or through observing members in one's social network – is taking place. As in trait-based models, the predominant technologies studied in social network analysis are genetically modified and high yield seed varieties. Foster and Rosenzweig (1995) develop a Bayesian model to study the adoption of high-yield seed varieties during the Green Revolution in India. They find adoption of high-yield varieties is positively correlated with the extent of prior adoption by other residents of the same village. Maertens and Barrett (2012) study the adoption of Bt cotton in farm households in a semi-arid region of India. After performing a probit regression, they find that living near another farmer, having a field near another farmer's field or even regularly passing another farmer's field increases the likelihood of a link by 20 to 50 percent. They also find that the likelihood of a factor influencing a link is village-specific. For example, education of the head of household increases the likelihood of a link in only one of the three villages surveyed.

18. Summary and implications for the southwestern US

18.1 Crop simulations

Crop simulation studies suggest that yields are highly dependent on the given crop and climate variable studied. In general, horticultural crops are more sensitive to short-term environmental stresses than field crops (Jackson et al. 2011). In California, observational data suggests warmer seasonal nighttime temperatures have increased yields of wine and table grapes, but decreased yields of avocados, walnuts, and almonds (Table 2). Higher seasonal precipitation has led to increased yields of wine and table grapes, almonds, strawberries, and Valencia oranges. The data suggest that the effect of warmer temperatures is highly seasonal for many crops; i.e., there are seasons during which warming is particularly harmful. Cherries, however, appear to be harmed by warming throughout the year (Lobell and Field 2011). However, higher seasonal precipitation has no observable effect on the other crops as shown in Table 2. Climate projections suggest that many crops will exhibit decreases in yield, with the exception of alfalfa and almonds (Lee, De Gryze and Six 2011; Lobell and Field 2011). Jackson et al. (2011) study the influence of extreme events on six crops (alfalfa, maize, rice, sunflower, tomato, and wheat) in Yolo County, California. Heat waves in May reduce yield for all crops except alfalfa and wheat. Repeated heat waves create an even more pronounced decline in yield. More studies in the region need to incorporate the effects of CO_2 fertilization effects and the impacts of climate variability.

18.2 Economic optimization

Mathematical programming and econometric approaches have been applied to the southwestern United States. Two major programming models that have been applied to study climatic impacts on agriculture in California are the SWAP (Howitt and Pienaar 2006) and USARM (Frisvold and Konyar 2012) models. The results from the SWAP model under two different GCMs suggest that California agriculture (and potentially agriculture in other southwestern states that are water-constrained) will shift from low (e.g., pasture, field, and grain crops) to higher value crops under climate-induced water shortages (Medellin-Azuara et al. 2011; Howitt and Pienaar 2006). For example, pasture declines by over 90 percent in Sacramento, San Joaquin, and Southern California by 2050 under the GFDL climate model (Medellin-Azuara et al. 2011). Medellin-Azuara et al. (2011) also find that Sacramento and San Joaquin regions exhibit the largest decline in low-value crops. The results from the USARM simulation model also indicate an acreage reduction in lower-value crops, particularly alfalfa and cotton. Acreage of specialty crops has negligible change in the simulation (Frisvold and Konyar 2012).

Econometric approaches tease out the direct statistical influence of climate on farmland value, or net farm revenue. The classic Ricardian paper (Mendelsohn, Nordhaus, and Shaw 1994) finds that climate variables (temperature and precipitation) have a negative impact on U.S. farmland values. Subsequent studies find that precipitation is not statistically significant in largely irrigated areas (Schlenker et al. 2006; Schlenker et al. 2005). Other studies find a statistical relationship between access to surface water and farmland value (Schlenker et al. 2007; Mendelsohn and Dinar 2003), though this relationship diminishes as water becomes more abundant.

18.3 Adaptation studies

Classic technology adoption papers have indicated that technology has been used to substitute for some natural deficit, such as a soil’s water-holding capacity (Caswell and Zilberman 1986; Negri and Brooks 1990). Studies have found that adaptation reduces losses from climate change. Using the WEAP model, Purkey et al. (2008) find that the combined effect of improved irrigation technologies and shifting cropping patterns reduces future increases in water demand to their current level. Without such adaptations, water demand increased through the twenty-first century. Frisvold and Konyar (2011) find that including adaptations (i.e., shifting between irrigated and rainfed production, altering water use on irrigated acreage, altering use of inputs on planted acres, fallowing land, and changing the crop mix) reduces the cost of water shortages to producers by 66 percent as compared to a simulation with fallowing alone. The other adaption studies that study farmer choice have not been implemented in the Southwest, but it would benefit the region to conduct such studies.

18.4 Implications

There is no “best” approach to modeling the climate-induced economic impacts on agricultural yield. This is likely even the wrong methodology (Mendelsohn and Dinar 2009; Adams 1999). A review of the different modeling approaches provides the researcher with options for the most suitable approach or approaches. Indeed some models incorporate more than one approach (e.g., Connor et al. 2009). Mendelsohn and Dinar (2009) suggest that studies from different authors using different modeling frameworks could complement one another. For example, consensus from different methodologies on regions that are sensitive to climate could add weight to creating effective policies in these regions. And, indeed there is consensus among economic modeling approaches, and between economic and crop simulation approaches that certain crops will be adversely affected directly by increasing temperatures, and indirectly through temperature effects on water availability and timing. This, in turn, affects agricultural land values, as shown by the econometric studies. The mathematical programming approaches suggest that, without adaptations, irrigated acreage will decline in the present century. The studies that attempt to understand farmer incentives to adopt technologies or management practices will provide additional insights to which technologies and practices may be adopted in the future.

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Tables and Figure

Table 1: Crop models used for estimation of possible climate change on agricultural yields.

Model	Description
CERES	Describes daily development and growth in response to enviro factors (soils, weather and management). It uses the Priestley-Taylor (1972) method of estimating potential evapotranspiration.
EPIC	Developed by the USDA to analyze the relationship between soil erosion and agricultural yield at the field level. Later versions of the model have incorporated a CO2 function for climate change assessments.
WOFOST	Created by de Wit (1965). Estimates biophysical variables (e.g., biomass production, crop development stage, time of maturation) related to crop yield.
CropSyst	Multi-year, multi-crop daily time step cropping system model. It consists of a group of programs that operate together to allow analyses of crop rotations at various temporal and spatial scales.
DSSAT	Computer-based decision support system that includes crop models and tools for analyzing climate inputs, model results, and management strategies.
WEAP	Integrated decision support system designed to support water planning that balances water supplies generated through watershed-scale physical hydrologic processes and multiple water demands and environmental requirements.
CROPWAT	Irrigation management model developed by FAO to calculate regional crop water and irrigation requirements.
WATBAL	Evaluates climate change impacts on river basin runoff.

Source: Data taken from Iglesias et al. (2011) and Rosenzweig et al. (2004)

Table 2: Observational trends between crop and climate variable in California

Crop	Yield Impact	Climate Variables
wine grapes	increase	warm nighttime temperatures in April, and higher rainfall in June
lettuce	increase	warm daytime temperatures in April and October
almonds	decrease	warm nighttime temperatures in February, increase in January precipitation
strawberries	increase	low Tmax and high precipitation in Nov.
table grapes	increase	increase in October precipitation, warmer nighttime July temperatures
Valencia oranges	increase	increase in May precipitation
Navel &Valencia oranges	decrease	low Tmin in December & March
cotton	increase	warm May Tmax
tomato	increase	warm April & June Tmax
walnuts	decrease	warm daytime Nov, warm nighttime Feb
avocado	decrease	warm nighttime temperatures in May, warm daytime temperatures in August

Source: Lobell et al. 2007

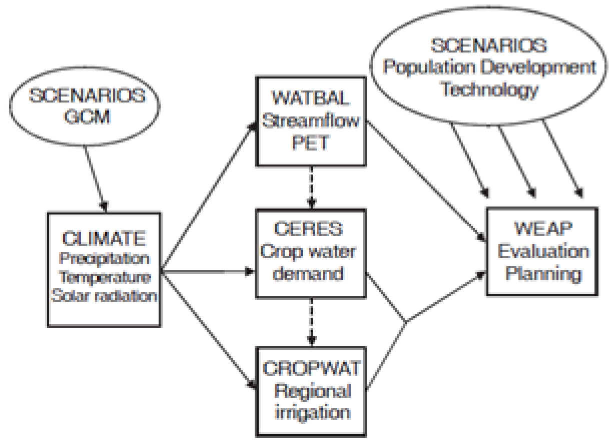

Figure 1: Basic integrated modeling framework.

Source: Rosenzweig et al. (2004)