Impact of Climate Change on Storage Conditions for Major Agricultural Commodities across the Contiguous United States

by

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Abstract

Climate change is a well-documented phenomenon with the potential to negatively impact both quantity and quality of agricultural commodities. To feed a growing population and maintain storage cost-effectiveness, it is vitally important to reduce postharvest crop losses. Postharvest crops requiring preservation are sent to cold storage facilities until needed by the agricultural marketplace. This study will focus on cold storage facilities across the contiguous United States and will analyze both historical temperature conditions during years 1979-2019 and the potential impact of increasing temperatures on future storage conditions during years 2020-2080.

The first chapter of this thesis assesses the impact of increasing temperatures on cold storage conditions for seven crops across the contiguous United States (CONUS). Projected simulations from 20 global circulation models (GCMs) forced by two representative concentration pathways (RCPs) were analyzed for the nine climatically consistent regions in the U.S. When compared to the historical reference period, all regions are projected to have significant negative impacts on both storage degree day (SDD) accumulation and winter length. If atmospheric CO2 levels continue to increase in the future, this research concludes that cold storage conditions will change and will increase energy costs for storage facilities and may affect future food availability.

The second chapter further analyzes chapter one results and identifies future prospectives in research. Identification in projected storage changes is necessary information for storage facilities so that preparations can be discussed by agriculturalists. Inclusion of other impacts accelerated by climate change (e.g., yield loss, harvest season variations, or land use change)

could increase the impactfulness of this study and are discussed in chapter two. Regardless of climate change impact study, reducing uncertainty in projections is increasingly necessary for regional and national agricultural planning. Conclusion of chapter two will identify mechanisms and technology available for downscaling coarse climate data for better predictions.

The findings from this work have implications for improving yearly forecasting of SDDs requirements, winter storage conditions, and potential energy costs for storage of seven different crops around the U.S. These forecasts can be beneficial to cold storage operators, farmers, policymakers, and various stakeholders as preparations are made for increasing temperatures. To expand on these findings, future work can investigate new technology installed in cold storage facilities (e.g, forced-air ventilation or advanced computer software). Inclusion of crop yield changes along with crop storage changes would allow for much better decision making when planning for future climate scenarios. Addition of other environmental data allows for interdisciplinary studies with soil, water, and health-related fields. These additional measures would further contribute to the understanding and improvement of yearly forecasting of storage conditions in the contiguous U.S.

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List of Abbreviations

CA	Controlled atmosphere
CONUS	Contiguous United States
CSA	Climate-smart agriculture
CMIP	Coupled Model Intercomparison Project
EPA	Environmental Protection Agency
FAS	Foreign Agricultural Service
GCM	Global circulation model
GHG	Greenhouse gas
IARW	International Association of Refrigerated Warehouses
IPCC	Intergovernmental Panel on Climate Change
MIP	Model Intercomparison Project
RCM	Regional Climate Model
RCP	Representative concentration pathway
RH	Relative humidity
SDD	Storage degree day
Tmax	Maximum temperature
Tmin	Minimum temperature
WHO	World Health Organization
WMO	World Meteorological Organization
UNEP	United Nations Environment Program
U.S.	United States

USDA	United States Department of Agriculture

Chapter 1
Literature Review

Motivation

Climate change, expressed as elevated temperatures caused by increasing atmospheric CO_2 concentrations, is expected to affect both crop yield and storage through commodity losses and additional energy requirements. Higher temperatures can increase food insecurity by reducing crop yields or through postharvest losses of disease and infestation. Worldwide estimates by the United Nations indicated that in 2016 and 2018, one-third of all food was lost or wasted and 9.2 percent of the world population experienced severe levels of food insecurity respectively (FAO 2019; Nations 2016). The United States (U.S.) population is expected to continuously grow over the next 40 years; therefore, researchers must identify how climate change will impact agricultural production and storage. The U.S. Census Bureau estimates that the U.S. population could be anywhere from 403.7 million to more than 416.8 million individuals by the year 2060 (Colby and Ortman 2015; Rubenstein 2016). Numerous studies have evaluated the impact of elevated temperatures on crop growth and yield, but current scientific literature has not properly addressed the impacts of elevated temperatures on crop storage. Previously cited reports by U.S. Census Bureau and United Nations support the theories that 1) current agricultural practices can become more efficient 2) changes in crop yield or storage could have detrimental effects on global food stocks and human welfare. Although we have greatly reduced the number of those suffering from food insecurity since the World Health Organization's (WHO) establishment in 1948, increases in agricultural storage efficiency have the potential to greatly decrease this worldwide epidemic – starting with a more thorough understanding of agricultural storage in the CONUS.

Agriculture & Climate Change

On a molecular level, food produced by farmers provides nutrients, minerals, and energy that are necessary for cellular processes to occur; thereby ensuring a humans' survival. U.S. agricultural farm output in 2017 accounted for nearly $132.8 billion of the country's gross domestic product with an additional $900 billion generated through business sectors related to agriculture (Morrison et al. 2019). Crops are generally sold in local markets or purchased by larger corporations for mass distribution but increases in international commerce have changed how agriculturalists can conduct business. Along with generating sustenance for the United States population, globalization in trade has created an advantageous platform for increasing profits and creating a steady supply of commodities to needy areas at appropriate times. The primary advantage of international trade is that agricultural products can generally acquire the best-selling prices due to competition and breakdown of domestic monopolies. But the logistics of long-distance international trade is highly dependent upon products being stored using the appropriate chemicals, machinery, and facilities. Products must remain below specific temperature thresholds to reduce disease and remain viable for human consumption; therefore, cold storage is a necessary requirement to extend the longevity of crops. The U.S. Department of Agriculture's (USDA's) Foreign Agricultural Service (FAS) reports that nearly 20% of domestic production volume is exported to foreign countries each year (NALC 2019). These production and export values clearly show that international agricultural trade is a viable option for U.S. farmers, but changes in product supply may affect the global marketplace.

Prior to crops being subjected to storage, they first must be cultivated by farmers under a set of demanding conditions that differ by geographic location. A non-comprehensive list of pressures affecting crop maturation include nutrient limitation, inadequate sunlight, pest infestation, microbial disease, insufficient humidity, and extreme temperature events (Aggarwal et al. 2006; Harel et al. 2013; Hernández et al. 2015; Soliman et al. 2012). If even one of these factors is askew from "normal" conditions, crop yield may be affected and this may have an impact on food stocks for storage. Additional studies have shown that elevated temperature rates decrease the productivity of certain crop species including maize, potatoes, and rice (Cammarano and Tian 2018; Raymundo et al. 2018; Singh et al. 2017). These three crops are considered leading staple food crops and make up the dominant part of many a population's diet (Sue et al. 2014). Current U.S. agricultural yields are sufficient for feeding the population, but increases in population, temperatures, storage costs, or postharvest losses could have a detrimental effect on U.S. agroeconomics. Since prior studies have already looked at crop yield changes as a function of temperature, this new study was conducted to look at cold storage changes as a function of temperature.

For climate change to be present, multi-decadal shifts in weather patterns that alter temperature and hydrology must be observed. These shifts are controlled by external forcings and internal feedbacks including but not limited to: solar radiation exposure, greenhouse gas (GHG) concentrations (land, ocean, and atmosphere), wind direction and strength, Milankovitch cycles, and geography (Ackerly et al. 2010; Bauer et al. 2003; Pielke et al. 2009; Spiegel et al. 2010; Sydeman et al. 2014). These forcings and feedbacks are dynamically linked so that a change in any of the aforementioned factors may greatly influence another factor. Humans have little impact on natural external forcings of climate change (e.g, solar radiation variability), but humans do have a large impact on externally forced GHG emissions and land use changes. Current news sources and scientists have reported that global temperatures are increasing and will continue to increase due in part to greenhouse gas emissions (Allen et al. 2009; Fountain 2019; Gordon and Lewis 2017). With climate anomalies expected to become more frequent, additional research must be conducted to evaluate the potential changes of temperature on agricultural storage.

Global climate change and agriculture have been internationally researched since 1988 when the Intergovernmental Panel on Climate Change (IPCC) was established by the United Nations Environment Program (UNEP) and the World Meteorological Organization (WMO) for assessing the science related to climate change and making this information available to policymakers (IPCC 2019). In the 2014 IPCC Fifth Assessment Working Synthesis Report, collected temperature data supported the theory that global averages in the atmosphere and ocean are increasing at an alarmingly high rate (IPCC 2014b). With these increasing global averages, water resources will become more limiting and there is an increased likelihood for crop failures; therefore, conserving surplus crop yields will become increasingly important for the worldwide economy. Despite understanding the value and necessity of crop storage, the IPCC Synthesis Report contains very little advice or information on the impacts of climate change on storage. Their industrial mitigation measures were primarily focused on reduction of greenhouse gases, improved energy efficiency, increased recyclables, and decreased tax revenues. Energy efficient technology is a viable option to reduce energy costs, but these new systems can be very expensive or difficult to incorporate. The measures proposed by the IPCC should be seriously considered for implementation, but the measures do not adequately address the impact of temperature on storage if (a) GHG emission minimums are not met and (b) new technology is not implemented. Therefore, an impact analysis must be conducted into changing storage conditions (regardless of technology) around the U.S. so that agriculturalists can make necessary accommodations for future scenarios.

GHGs, CO2, and Increasing Temperatures

Evaluating why climates change and their impact on agriculture is highly dependent upon which external feedback or internal forcing mechanism is predominant in that geographical locale. Humans can exacerbate climate change through excessive GHG emissions by burning fossil fuels, clearing forest land, or changing local hydrology. Atmospheric CO2 has been cited by the Environmental Protection Agency (EPA) as the primary greenhouse gas influencing the recent increase in global temperatures (EPA 2016). Scientists have deduced that anthropogenic atmospheric CO2 has been rapidly accumulating since the Industrial Revolution in the late 1800s and global average atmospheric rates as of 2018 were 407.4ppm +/- 0.1ppm (Lindsey 2019). These are abnormally high atmospheric concentrations, but it is important to note that CO2 is also naturally produced during animal respiration, decay of organic matter, rock weathering, or volcanic eruptions (CSI 2016). Despite these natural emissions, natural carbon sequestration methods (e.g., plants, soils, and oceans) are not able to store all the excessive CO2 produced from anthropogenic sources. The continued release of natural CO2 in conjunction with human produced CO2 may have devastating effects on global temperature rates; thus affecting postharvest losses and storage costs.

CO2 is the primary GHG of this study and is a major contributor to rising temperatures because of its atomic structure and ability to absorb infrared wavelengths emitted by the sun around 15μm (Zhong and Haigh 2016). These chemical characteristics, along with their high concentrations, have the potential to exacerbate global climate anomalies by retaining excessive solar radiation. But CO_2 is not the sole GHG contributor affecting global climates, it is just the major contributor at present times. Additional major GHGs that can trap heat energy include nitrous oxide (N_2O), tropospheric ozone (O_3), hydrofluorocarbons (HFCs), methane (CH_4), and water vapor (EPA 2017). Since the first IPCC meeting in 1988, collaborators around the world have modeled various concentrations of major GHGs and their potential effects on temperature (Banger 2015; Fuhrer 2003; Ravishankara et al. 2009; Solomon et al. 2010; Wu et al. 2014). These modeling studies show a positive correlation over time between GHG concentrations and temperatures, but further analyses into which economic sectors emit GHGs provides an interesting irony – agriculture may be harming itself in a positive feedback loop.

The IPCC 2014 Working Group III Report identified that nearly 24% of GHG emissions were generated by agriculture, forestry, and other land use sectors (IPCC 2014a). The remaining 76% of anthropogenic GHG emissions are contributed primarily by electricity and heat production, industry, transportation, other energy, and buildings, respectively. One study has shown that sustainable agriculture for increasing populations creates a positive feedback loop for CO_2 accumulation in the atmosphere through deforestation, loss of natural habitats, and fuel consumption (Bajželj and Richards 2014). Inference from this report and crop yield studies can help one to deduce an interesting problem in agriculture. By clearing more land for agriculture and industry, more CO_2 is released into the atmosphere and less can be stored in plant and soils. Forests and other natural habitats are generally considered sinks of carbon and when properly conserved these ecosystems can greatly offset atmospheric CO_2 levels and reduce global temperatures (McGarvey et al. 2015). Excess CO_2 accumulates in the atmosphere and leads to an increase in temperatures that affect future crop yields and can increase storage costs – both of which can affect food insecurity. A worst-case scenario would be the elimination of forests for agricultural land, but our crop yields are similar and storage costs are higher due to increased temperatures. Although forested ecosystems can greatly offset the CO_2 concentrations, reforestation efforts may conflict with crop producers who need greater land area to produce more crops for an expanding population.

To combat the challenging issue of GHG emissions, the 2015 United Nations Climate Change Conference was held in Paris, France to negotiate binding, universal agreements on climate between concerned countries. More than 190 countries, including the U.S., signed Intended Nationally Determined Contributions to specify how they could reduce their GHG emissions and a call to action was given (U.N. 2015). Unfortunately, news reports state that the resolutions passed by the Conference Committees have yet to be maintained by almost any country. In October 2019, The American Prospect reports that only one country has kept their promised resolutions – the country of Morocco (Gibson 2019). All other industrialized nations have failed to uphold to their agreements and Gibson states that nothing will likely change in the near future. Another article from the Los Angeles Times details how the most recent Climate Conference in Madrid was also a bust (Board 2019). The report states that delegates and international leaders from industrialized nations were more apathetic to make changes than the smaller countries. This study on crop storage will be greatly beneficial in the event that U.S. temperatures continue to rise due a continued increase in global GHG emissions.

Cold Storage

Cold storage and has been proven as an effective means of increasing the shelf life of many agricultural commodities and can offset potential losses when crop yields oversaturate the fresh market (Colombo et al. 2018; Fuglie 1999; Khanal and Uprety 2014; Phyo et al. 2004). Cold storage is one portion of what is commercially known as the “cold chain”. The optimal cold chain involves a sequence of transport and storage phases that keep commodities in an unbroken "chain" which can drastically decrease crop losses due to tissue degradation (Montanari 2008). Increases in crop longevity differ by crop species (e.g., short term, medium-term, long-term) and these increased marketability times provide monetary benefits to both farmers and consumers. Cold storage is an energy-intensive process that generally utilizes electrical energy to maintain cooling operations. Typically, more than 54% of all energy used in a cold storage facility is used on refrigeration alone (EnergyTrust 2014). External temperatures directly affect internal temperatures through conduction; therefore, more energy will be required if external temperatures are higher than inside temperatures.

Studies conducted within the U.S. have identified how climate change will influence crop production rates based upon projected climate scenarios (Cammarano and Tian 2018; Raymundo et al. 2018; Singh et al. 2017), but these studies do not look at postharvest cold storage conditions for those crops on a country-wide scale. Other scientific studies also look at how we can improve the crop's genetics to overcome cold storage difficulties (Cardi and Varshney 2016; Clasen et al. 2016), but these improvements may be null if storage facilities are not updated with proper machinery. High costs associated with new technology and/or retrofitting may inhibit companies from investing in the newest technologies, but new research can inform all agriculturalists of predicted changes. Additionally, some studies conducted on cold storage are studied in countries outside the U.S. and may not be relevant due to varying regional climate conditions or crop varieties analyzed (Usall et al. 2015; Wang et al. 2017). Reference studies show that changes in agricultural storage need to be more understood and these changes quantified to identify specific impacted sectors. Although storage facilities vary by size, cooling condition treatments, and types of products stored, these facilities all share an important goal – reducing food insecurity by commodity preservation.

Climatology of the United States

Depending upon the purpose of study, the CONUS can be divided into different regions based upon specific conditions of interest. CONUS regional divisions can be made in watersheds, climate, ancestry, ecoregions, or other categorical variables (Karl and Koss 1984; Lubin 2016; USDA 1994; USGS 2019). When evaluating climate changes within the U.S., research by Karl and Koss (1984) is a widely used climate reference supported by the National Atmospheric and Atmospheric Administration (NOAA) (Figure 1.1). Based upon climate data from 1895-1983, Karl and Koss identified 9 climatically consistent regions based upon similar temperature and precipitation patterns. This map can be used to assess how current climate anomalies compare with historical climate events due to its extensive temperature dataset with the contiguous United States. Changes in one state can also be generalized for the entire region; therefore, large scale analyses can be conducted with localized temperature data.

Objectives

Impacts on agricultural storage due to increasing temperatures have not been analyzed at regional levels across the continuous U.S. This thesis focuses on analyzing the impacts on storage degree day accumulation and length of winter subperiod for hub crops in each climatically consistent region in the U.S. The first chapter of this paper will identify changes in projected storage conditions compared to the historical reference period. Additionally, strategies must be identified as agriculturalists prepare for increasing temperatures caused by climate change. This will be accomplished by addressing three objectives: (1) analyze historical winter storage conditions for each climate region; (2) measure projected changes in SDD accumulation and winter length for each climate region; (3) and provide informed strategies to stakeholders regarding conditions predicted under future climate scenarios.

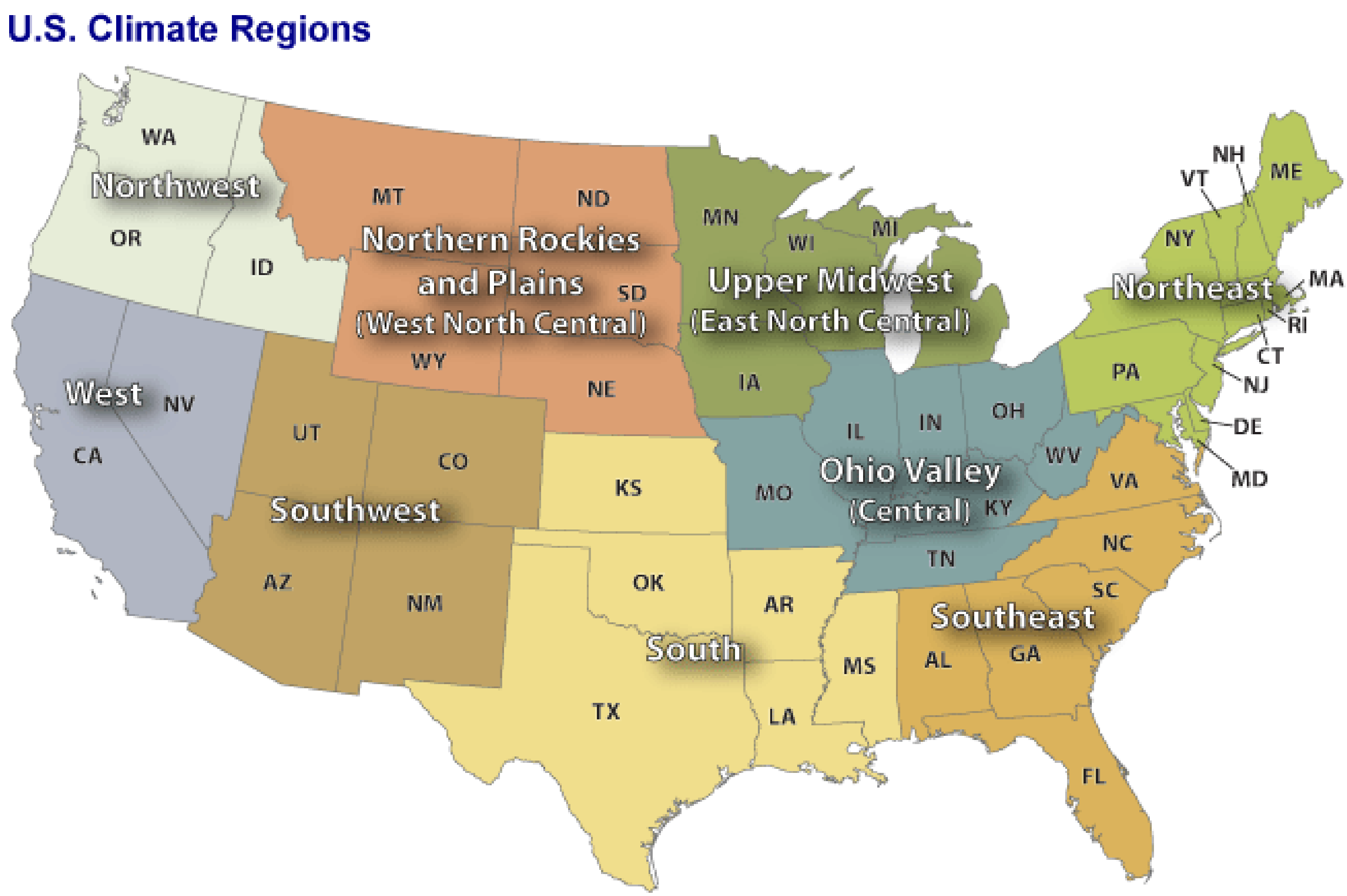

Figure 1.1 Climatically consistent regions within the contiguous United States. Thomas R. Karl and Walter James Koss, 1984: *"Regional and National Monthly, Seasonal, and Annual Temperature Weighted by Area, 1895-1983."* Historical Climatology Series 4-3, National Climatic Data Center, Asheville, NC, 38 pp.

Chapter 2
Impact of Climate Change on Storage Conditions for Major Agricultural Commodities across the Contiguous United States

(This chapter has submitted for publication in Climatic Change Journal)

Abstract

Changes in postharvest storage conditions due to climate change can directly affect energy usage and food supply and quality. However, no study has assessed climate change impacts on postharvest storage conditions in different climate regions over the contiguous United States (CONUS), a major agricultural producer around the world. The goal of this study is to assess the impact of climate change on cold storage conditions for the highest grossing crop for each of the nine climate regions within the CONUS. Storage degree days (SDDs) accumulate when ambient temperatures increase relative to crop storage base temperatures. Changes in SDDs and winter subperiod length were calculated for each regional crop using historical climate data and 20 downscaled global climate model projections. All regions project significant increases in SDD accumulation and decreases in winter subperiod length when compared to the historical reference period (1979-2019). Between years 2020-2080, Northwest and Northeast regions' apples will be impacted most by SDD accumulation with yearly increases between 341-1046 SDDs. Between years 2020-2080, Northern Rockies and Plains regions' potatoes are projected to lose the most days of winter (15-27 days), and Southeast regions' peanuts will experience the greatest decrease in winter length (16-21%). Increases in SDD accumulation and decreases in winter length will have direct implications on future food supply and storage costs. This study is the first comprehensive analysis of climate change impacts on the storage conditions for agricultural

commodities over heterogenous climate conditions at national scale, providing useful information for long-term agricultural storage planning.

1. Introduction

Increased ambient land temperatures due to anthropogenic increases in atmospheric CO2 concentrations have the potential to threaten the entire food supply chain beginning with crop development and yield (Cammarano and Tian 2018; Chin et al. 2018; Raymundo et al. 2018; Singh et al. 2017), through food cold chain transport (James and James 2010), and into postharvest long-term storage (Winkler et al. 2018). Increased growing season temperatures and time of harvest have the potential to directly affect crop integrity and postharvest processing and storage, which both ultimately affect crop quality (Mutegi et al. 2013; Paull 1998). Microbes begin to degrade soft tissues once crops are harvested, and increasing temperatures will increase microbial activity and spoilage in crops based upon the Q10 temperature effect (Watson et al. 2016). This Q10 effect refers to changes in metabolic activity and a 10°C increase in temperatures will cause a doubling or tripling of microbial activity which would increase infection or rotting rates (Bron et al. 2005). Therefore, once crops are harvested, it is imperative that they are subjected to their proper storage base temperature conditions to prevent accelerated degradation. The storage base temperature is not the same for all crops and optimal storage temperatures ensure prolonged quality of agricultural commodities (Krishnakumar 2002).

Under cold storage conditions, temperature will continue to affect crop quality and increasing ambient temperatures may exacerbate postharvest losses (James and James 2010). Crop storage is necessary to ensure a steady flow of product into the agricultural marketplace, but crop storage is also equally valuable as a mitigation factor against shortage of food supply (Bediako et al. 2009). If seasonal crop yields are lower than anticipated, crops in cold storage may be able to offset the seasonal losses – ensuring sufficient food supply. In a study focused in the state of Michigan, USA, Winkler et al. (2018) suggests that increasing temperatures will lead to an increase in storage degree day (SDD) accumulation and a decrease in length of winter subperiod for potato storage. In their study, SDDs are accumulated whenever ambient temperatures are higher than the storage base temperature required for potatoes (12°C for the first 8 weeks and then lowered by 0.1°C per day to 8°C). SDDs can be viewed as indicators for additional energy requirements needed to maintain the storage facility at a specific base temperature (Winkler et al. 2018). Therefore, an increase in SDD accumulation has the potential to decrease the ability of a storage facility to effectively store their crops outside of the growing season. The length of the winter subperiod describes the amount of time that agricultural commodities, potato in the case of Winkler et al. (2018), can be stored at relatively low cost since ambient temperatures are below the storage base temperature. Data from Winkler et al. (2018) gives valuable insight into the effects of climate change on crop storage, but focused only on a single crop (potato) in a single state (Michigan) with relatively higher base temperature and longer winter period. Changes in SDD accumulation and length of winter subperiod can vary by crop types and regions with different climate conditions; therefore, further study is needed to understand the historical and future climate impacts on crop storage conditions for different crops in different climate regions across the CONUS.

In order to understand future climate change impacts on crop storage, we need to utilize climate models to obtain projections of future temperatures. Global circulation models (GCMs) are physical-based mathematical models that are routinely used for projecting future climate with different scenarios of greenhouse gas (GHG) concentrations (Akinsanola et al. 2018; Ertugrul 2019; Parrish and Peterson 1988). GCMs used in the fifth Intergovernmental Panel on Climate Change (IPCC) report are forced through representative concentration pathways (RCPs) to simulate future climate. These RCPs represent solar radiative forcing, depending on projected GHG concentrations, which can be influenced by both anthropogenic and natural sources (van

Vuuren et al. 2011). GCMs are imperfect representations of the climate system. They are global-scale models running at coarse resolutions and the physical processes at local scale are highly parameterized, requiring bias correction and downscaling for reliable regional impact analyses (Fowler et al. 2007). When a sufficiently large number of GCMs are considered, bias of climate projections due to a single or few GCMs will be minimized because the uncertainty of climate projections can be quantified (Tebaldi and Knutti 2007).

Storage conditions of different crops may vary under different regions and climate conditions, and the response to the changes of ambient temperature may also be different. Therefore, this study aims to assess the climate impacts on cold storage conditions of major crops in different climate regions across the CONUS, one of the largest agricultural producers around the world. This study is the first to analyze impacts of climate change on crop storage conditions for different major crops at the national scale with high variability of agricultural and climate conditions. The knowledge gained in this study will be helpful for long-term agricultural storage planning.

2. Materials and Methods

2.1 Study Area and Crop Selection

This study focuses on nine climate regions (Karl and Koss 1984) over the CONUS (Figure 2.1). Karl & Koss (1984) identified climate regions by taking the areal weighted average of recorded temperature and precipitation distributions between years 1895-1983 for each state. Contiguous states with similar patterns and weightings were then grouped together to form climatically consistent regions. Each climate region has relatively homogenous climate conditions and states within each region have similar temperature and precipitation patterns. The highest grossing crop that requires cold storage was identified for each state using the state 2017 USDA

NASS survey report (USDA 2018). High grossing commercial crops that do not require cold storage were excluded from analysis including: barley, beans, canola, coffee, cotton, hay & haylage, hops, macadamias, maize, millet, mint, oats, peas, rice, rye, safflower, sorghum, soybeans, sunflower, taro, tobacco, and wheat. The cumulative crop value from all states within each climate region was then calculated and the highest grossing crop was selected for cold storage analysis (Table 2.1).

Identification of proper base temperature and storage dates is crucial to estimate cold storage conditions for different crops based on SDDs and length of winter subperiod. Information about the most common crop cultivar, harvest, and storage conditions for each climate region (Table 2.2) was obtained directly from University of Georgia Extension (UGA 2019), University of California Extension (UC 2019), scientific journal publications (Bohl and Johnson 2010; Butts et al. 2017; Kerns et al. 1999), North Dakota State Seed Department (ND.gov 2019), cold storage facility personnel, and the USDA-ARS agriculture handbook number 66 (USDA 2016).

2.2 Historical Climate Data

Historical daily maximum temperature (Tmax) and minimum temperature (Tmin) for years 1979-2019 was extracted from the gridMET database (Abatzoglou 2013) (available at http://www.climatologylab.org/gridmet.html) at the location of the representative storage facility for each region (the coordinates can be found in Table 2.2). The 40-year time slice (1979-2019) is sufficiently long enough for an accurate calculation of climatological means and changes in climate conditions (Winkler et al. 2018). The horizontal resolution for gridMET historical data was at ~4km or 1/24th degree over the CONUS. This data was produced from gridded parameter-elevation regressions on independent slopes model (PRISM) data blended with temporal attributes from North American Land Data Assimilation System (NLDAS-2) regional analysis. The gridMET data has been validated against in situ observations and widely used in climate impact studies, such as wildfires (Abatzoglou and Williams 2016; Barbero et al. 2015), crop evapotranspiration (Pereira et al. 2015), and rain-snow transition zones (Klos et al. 2014).

2.3 Future Climate Projections

The 20 statistically downscaled Coupled Model Intercomparison Project Phase 5 (CMIP5) GCMs Tmax and Tmin daily projections from years 2020-2080 were derived from the MACAv2 database (Abatzoglou and Brown 2012), at http://www.climatologylab.org/maca.html. Projected temperature data were extracted at the location of the representative storage facility for each region, as identified in Table 2.2. The horizontal resolution for MACAv2 projected GCMs were generated at ~4km or 1/24th degree and over the CONUS. The 20 downscaled GCMs ensembles (Table 2.3) included future scenarios forced by two different RCPs, namely RCP4.5 and RCP8.5. For RCP4.5, CO2 concentrations peak around 2040 with an atmospheric concentration ~ 650ppm; for RCP8.5, CO2 concentrations rise until the end of the twenty-first century and peak at ~1370ppm (Moss et al. 2010). Projected climate data was divided into 3 time slices for analysis: early-century (2020-2040), mid-century (2040-2060), and late-century (2060-2080). For each study site, a total of 40 climate projections (20 models x 2 RCPs) of daily Tmax and Tmin were used for each future time slice in comparison with the historical time slice (1979-2019). A 2012)

2.4 Calculation of SDDs and Length of Winter Subperiod

One index used to measure the impact of increasing temperatures on regional cold storage conditions was SDD. External energy will be required for cooling to compensate for the temperature gradient if the temperature on that day is above the base temperature. Therefore, daily incremental SDD (ΔSDD) for cold storage facilities can be calculated using the following formula:

$$\Delta SDD = max\left(\frac{T_{max_i} + T_{min_i}}{2} - T_{base}, 0\right)$$

SDD is calculated as the accumulation of ΔSDD over the storage period (Winkler et al. 2018). For each region, daily SDDs were calculated for (1) historical reference period (1979-2019); and (2) three future time slices mentioned above (2020-2040; 2040-2060; 2060-2080) using the downscaled temperature projections. SDDs were incrementally summed throughout the storage season and the daily values were smoothed using a 7-day moving average to minimize day-to-day fluctuations, as in Winkler et al. (2018). Historical SDD accumulation on the final day of storage and for each region, was used as a reference to compare against RCP4.5 and RCP8.5 GCM scenarios to determine future impacts.

The second index used to measure climate impacts on cold storage was the length of the winter subperiod which is considered as a continuous period with relatively cool temperature (i.e., little accumulation in SDDs) compared to the other periods. It is considered as a period in which storage costs are kept low since ambient temperatures can sufficiently cool stored crops (Winkler et al. 2018). For each region, the length of the winter subperiod was calculated for (1) historical reference period (1979-2019); and 2) three future time slices (2020-2040; 2040-2060; 2060-2080). The beginning and end of winter subperiod were identified by analyzing changes in daily SDD percentage accumulation rates. SDD percentage accumulation rates were calculated by looking at the SDD daily percentage total and taking a 7-day moving average to minimize day-to-day fluctuations (Winkler et al. 2018). The beginning of the winter subperiod for a particular year was defined as the first day in which the daily SDD accumulation fell below a 0.25% threshold for 14 days. The end of the winter subperiod for a particular year was similarly defined as the first day in which the daily SDD accumulation fell above a 0.25% threshold for 14 days. This 14-day criterion is used to minimize the influence of short-term warm or cold spells. The 14-day, 0.25% threshold was chosen due to past research utilizing this criterion based upon data for the northern United

States (Shabbbar and Bonsal 2003; Winkler et al. 2018). Similar to Winkler et al. (2018), we chose 14-day, 0.25% threshold in this study for convenience of spatial comparisons.

Using the aforementioned definition for beginning and ending of winter subperiod, 0.25% change for 14 days, the beginning and end dates of winter subperiod were tabulated. Next, the difference in the number of days between the beginning and end of winter was calculated. The average of the length of winter subperiod was calculated for the historical reference period of 1979-2019 and was compared against future RCP scenarios and time slices.

Projected storage parameters were calculated for each RCP/time slice for both changes in SDD accumulation and length of winter subperiod and compared to the historical reference period. For each RCP, all 20 GCMs were separated by time slice segments (early-, mid-, late-century) and the results were averaged to obtain the final mean value of all 20 GCMs for each time slice. Next, the difference in the climatological means between a future time slice and the historical reference period were calculated for each RCP and tested for statistical significance using a one-tailed, two-sample t-test assuming unequal variance with standard errors estimated using the Satterthwaite Approximation (Satterthwaite 1946).

3. Results

3.1 Increases in SDD Accumulation and SDD Percentage Change

SDD accumulation rates differed by region due to the length of the storage season, regional temperature values, and crop base temperature values. Historical SDD accumulation on the final day of storage and for each region, was used as a reference to compare against RCP4.5 and RCP8.5 GCM scenarios to determine future impacts (Figure 2.2). Each regional consecutive time slice contains higher SDD accumulation rates and percentage changes than the previous time slice (e.g., 2020-2040 < 2040-2060 < 2060-2080). All regions in RCP4.5 scenarios project a significant ($p < 0.05$) increase by the early-, mid-, and late-century time slice in mean SDD accumulation and SDD percentage change when compared to their historical reference period. For RCP4.5, mean SDD accumulation during the early-century range from a minimum increase of 54.7 SDDs in the West region (grapes) to a maximum increase of 355.7 SDDs in the Northeast region (apples) (Figure 2.3A,B,C), indicating higher storage costs. Mid-century changes range from a minimum increase of 108.5 SDDs in the Southwest region (lettuce) to a maximum increase of 546.6 SDDs in the Northeast region (apples). Late-century changes range from a minimum increase of 130.7 SDDs in the Southwest region (lettuce) to a maximum increase of 666.1 SDDs in the Northwest region (apples). When examining the yearly mean of all three future time slices (2020-2080), the Southwest region (lettuce) will be least impacted with an average yearly increase of 101.7 SDDs and Northeast region (apples) will be most impacted with an average yearly increase of 521.1 SDDs.

Uncertainty is inherent when assessing the future impacts of climate change and interpretation of ensembles must be conducted carefully (Winkler 2016). We only present the mean values of our GCM ensembles, but uncertainty in future SDD projections could allow for actual conditions to be higher or lower than our reported values. To address this uncertainty, Figures 2.4 - 2.12 display the maximum and minimum range for all GCMs for each RCP and time slice.

When looking at the percentage change in SDD accumulation for future time slices under RCP4.5 (Figure 2.13A,B,C), some regions appear to be impacted more despite having lower absolute rates of SDD accumulation (Figure 2.3A,B,C). Percentage changes reflect the percentage difference in SDD accumulation when comparing historical and future projections. Early-century changes in percentage difference in SDD accumulation range from a minimum increase of 4.3% in the West region (grapes) to a maximum increase of 26.3% in the Ohio Valley region (tomatoes). Mid-century changes range from a minimum increase of 8.8% in the West region (grapes) to a maximum increase of 37.9% in the Ohio Valley region (tomatoes). Late-century changes range from a minimum increase of 11.7% in the Southwest region (grapes) to a maximum increase of 46.9% in the Upper Midwest region (potatoes). When examining the yearly mean of all three future time slices, the West region (grapes) will be least impacted with an average yearly SDD increase of 8.5% while the Ohio Valley region (tomatoes) will be most impacted with an average yearly SDD increase of 36.2%.

All regions in RCP8.5 scenarios project significant ($p < 0.05$) increases in mean SDD accumulation by the early-, mid-, and late-century time slice when compared to their historical reference period (Figure 2.3D,E,F). Due to higher CO2 concentrations and the subsequent effect on atmospheric temperature, all RCP8.5 projections contain higher mean values than their respective RCP4.5 counterparts for each time slice for both SDD accumulation and percentage changes. Early-century changes in mean SDD accumulation range from a minimum increase of 70.8 SDDs in the West region (grapes) to a maximum increase of 386.7 SDDs in the Northwest region (apples). Mid-century changes range from a minimum increase of 143.5 SDDs in the Southwest region (lettuce) to a maximum increase of 674.1 SDDs in the Northeast region (apples). Late-century changes range from a minimum increase of 213.0 SDDs in the Southwest region (lettuce) to a maximum increase of 1045.0 SDDs in the Northeast region (apples). When examining the yearly mean of all three future time slices, the Southwest region (lettuce) will be least impacted with an average yearly increase of 145.9 SDDs and the Northeast region (apples) will be most impacted with an average yearly increase of 699.2 SDDs.

RCP8.5 early-century changes in percentage difference in SDD accumulation range from a minimum increase of 5.5% in the West region (grapes) to a maximum increase of 28.3% in the Ohio Valley region (tomatoes) (Figure 2.3D,E,F). Mid-century changes range from a minimum increase of 12.7% in the Southwest region (lettuce) to a maximum increase of 46.3% in the Ohio Valley region (tomatoes). Late-century changes range from a minimum increase of 18.3% in the Southwest region (lettuce) to a maximum increase of 64.8% in the Ohio Valley region (tomatoes). When examining the mean of all three future time slices, the Southwest region (lettuce) will be least impacted with an average SDD increase of 12.8% and the Ohio Valley region (tomatoes) will be most impacted with an average SDD increase of 46.5%.

3.2 Changes in Length of Winter Subperiod and Percentage Difference

The length of the winter subperiod was determined by percentage changes in SDD accumulation on a day-to-day basis. The historical and projected length of winter subperiod for all regions with an observable winter subperiod are provided in Figure 2.14. The Southwest and West regions did not have an observable winter subperiod. The Southwest region (lettuce) had a storage season of only 1 month for fall season and 1 month for spring season. Calculation of a winter subperiod is not feasible since the storage period is so short based on our beginning and end 14-day criteria. The West region (grapes) had a storage season of only 3 months and temperatures did not drop low enough in the storage period for a discernible winter subperiod.

Each regional consecutive time slice contains lower winter subperiod length and higher percentage changes than the previous time slice (e.g., 2020-2040 < 2040-2060 < 2060-2080). All regions with a winter subperiod in RCP4.5 scenarios project a significant ($\alpha = 0.05$) decrease by the early-, mid-, and late-century time slice in mean length of winter subperiod and winter percentage change compared to their historical reference period. Early-century decreases in mean length of winter subperiod range from the smallest loss of 3.9 days in the South region (peanuts) to the largest loss of 15.8 days in the Upper Midwest region (potatoes) (Figure 2.15A,B,C), indicating less cost-effective storage days. Mid-century decreases range from the smallest loss of 6 days in the South region (peanuts) to the largest loss of 18.7 days in the Upper Midwest region (potatoes). Late-century decreases range from the smallest loss of 7 days in the South region (peanuts) to the largest loss of 20.3 days in the Upper Midwest region (potatoes). When examining the yearly mean of early-, mid-, and late-century time slices (2020-2080), the South region (peanuts) will be least impacted with a yearly average loss of 5.3 winter days and the Upper Midwest region (potatoes) will be most impacted with a yearly loss of 18.3 winter days.

RCP4.5 early-century differences in percentage decrease in length of winter subperiod range from a minimum loss in winter days of 6.4% in the Northern Rockies and Plains region (potatoes) to a maximum loss of 16.6% in the Southeast region (peanuts) (Figure 2.16A,B,C). Mid-century differences range from a minimum loss of 7.3% in the Upper Midwest region (potatoes) to a maximum loss of 17.1% in the Southeast region (peanuts). Late-century differences range from a minimum loss of 7.8% in the Northern Rockies and Plains region (potatoes) to a maximum loss of 17.5% in the Southeast region (peanuts). When examining the yearly mean of all three future time slices, the Northern Rockies and Plains region (potatoes) will be least impacted with an average yearly decrease in winter length of 7.2% and the Southeast region (peanuts) will be most impacted with an average yearly decrease in winter length of 17.1%.

All regions in RCP8.5 project a significant ($\alpha = 0.05$) decrease by the early-, mid-, and late-century time slice in mean length of winter subperiod and winter length percentage change compared to the historical reference period. Due to higher CO2 concentrations, all RCP8.5 projections contain lower mean values than their respective RCP4.5 counterparts for each time slice for both length of winter subperiod and percentage changes. Early-century decreases in mean length of winter subperiod range from the smallest loss of 4.2 days in the South region (peanuts) to the largest loss of 15.9 days in the Upper Midwest region (potatoes) (Figure 2.15D,E,F). Mid-century decreases range from the smallest loss of 8.3 days in the South region (peanuts) to the largest loss of 21.8 days in the Upper Midwest region (potatoes). Late-century decreases range from the smallest loss of 10.2 days in the South region (peanuts) to the largest loss of 26.9 days in the Upper Midwest region (potatoes). When examining the yearly mean of all three future time slices, the South region (peanuts) will be least impacted with an average yearly loss of 7.6 days and the Upper Midwest region (potatoes) will be most impacted with an average yearly loss of 21.6 days.

RCP 8.5 early-century differences in percentage decrease in length of winter subperiod range from a minimum loss in winter days of 6.7% in the Upper Midwest region (potatoes) to a maximum loss of 16.4% in the Southeast region (peanuts) (Figure 2.16D,E,F). Mid-century differences in winter length range from a minimum loss of 8.1% in the Northern Rockies and Plains (potatoes) and the Upper Midwest region(s) (potatoes) to a maximum loss of 18.9% in the Southeast region (peanuts). Late-century decreases in winter length range from a minimum loss of 9.6% in the South region (peanuts) to a maximum loss of 20.6% in the Southeast region (peanuts). When examining the yearly mean of all three future time slices, the South region (peanuts) will be least impacted with an average yearly decrease in winter length of 8.2% and the Southeast region (peanuts) will be most impacted with an average yearly decrease in winter length of 18.6%.

4. Discussion

4.1 Most Impacted Crops and Regions in CONUS

All regions are anticipated to have yearly increases between 54-1045 SDDs. The largest impact in SDD accumulation occurs for apples in both Northwest and Northeast regions in all three time slices and both RCPs with yearly increases between 341-1045 SDDs. Increases in SDD accumulation in the Northwest and Northeast regions and the potential corresponding increase in storage costs may contribute to future apple scarcity since both regions combined contribute to over $3billion in apple sales annually (USDA 2018). These SDD increases during the Northeast storage season may be compounded by additional heat stress days incurred during the growing season, thus leading to a decrease in yield and increase in food scarcity (Wolfe et al. 2007).

SDD increases have a positive correlation with increasing temperatures and past research has identified that CONUS temperatures are expected to increase throughout the 21st century (Karmalkar and Bradley 2017; USGCRP 2014) as well as increasing heat stress in the South and Southeast regions which can affect negatively future crop yields (Weatherly and Rosenbaum 2017). Previous studies also showed that temperatures will continually increase in specific regions of the country including the Upper Midwest region (Hayhoe et al. 2010), Western and Northwest regions (Rupp et al. 2016), and Northeast region (Hristov et al. 2017). The percentage change in SDD accumulation also reflects changes in storage requirements and all regions are anticipated to have yearly SDD percentage increases between 4-65%. Although Northwest and Northeast regions (apples) will have the highest SDD accumulation increases, the largest percentage change in SDD accumulation occurs in the Ohio Valley (tomatoes) and the Upper Midwest (potatoes) for all three time slices. SDD percentage changes may reflect additional storage energy requirements affecting future storage costs and potentially decrease food availability (Hadley et al. 2006; McFarland et al. 2015).

Decreases in the length of winter subperiod affect the number of available days that crops can be stored at minimal costs (Winkler et al. 2018). The length of the winter subperiod is influenced by ambient temperatures (higher or lower) and not all regions will be equally affected by future changes in climate. Past research reiterates that climate change will reduce regional length and intensity of winter in the Upper Midwest (Chin et al. 2018), Northeast (Scott et al. 2008), and worldwide for fruit industries (Luedeling et al. 2011). Upper Midwest (potato) storage facilities will experience the highest loss of winter days for all three time slices and both RCPs (≈21.6 days each year). This implies that storage costs are expected to be much higher in this region under future scenarios since there are ~22 fewer cost-effective storage days. But when looking at percentage decrease in the length of winter subperiod, we find that the Southeast region (peanuts) will be the most affected out of all three time slices and both RCPs (~18.6% decrease each year). The Southeast region (peanuts) winter subperiod length was already shorter than any other region (historical average ~120 winter days), but future climate change will continue to reduce the winter subperiod length and may affect future food availability related to peanuts. Previous research suggests that increases in both CO2 and temperature will advance the maturation rates of peanuts (Noorhosseini et al. 2018). Earlier maturation and harvest of peanuts will require longer cold storage times and this will lead to an increase in SDD accumulation since storage needs to begin earlier. Although SDD accumulation changes do not directly affect length of winter subperiod, our research has shown that increasing temperatures will lead to an increase in SDD accumulation and a decrease in the winter subperiod (Figures 2.3 and 2.13 respectively). Coupled increases in SDD accumulation and decreases in winter subperiod length will lead to new fiscal challenges faced by agronomists as they attempt to increase adaptive resilience of agricultural systems to climate changes within the CONUS.

4.2 Potential costs associated with SDD Accumulation and Winter Subperiod Changes

This study demonstrates how changing climate can potentially impact crop storage conditions of agricultural commodities over the CONUS. All 9 regions in RCP4.5 and RCP8.5 models indicated an increase in SDD accumulation for early-, mid-, and late-century time slices and 7 regions projected a decrease in length of winter subperiod for early-, mid-, and late-century time slices. The exact cost of 1 SDD is likely dependent upon storage facility location, facility design, and temperature-control technology installed. Despite the difficulty of estimating the exact cost of 1 SDD increase, increases in temperature will have immediate impacts on storage costs over CONUS, varied by locations (Hadley et al. 2006; McFarland et al. 2015). Since storage facilities rely on external energy for refrigeration, increases in temperature will lead to an increase in energy required to maintain a constant base temperature (Saidur et al. 2002). Research performed by Jaglom et al. (2014) suggests that increasing temperatures will cost the U.S. power sector an additional $50 billion by 2050 and some of these costs will be incurred by the agricultural cold storage industries and ultimately consumers. When the length of the winter subperiod is shortened, additional costs will be incurred to maintain base temperature. Normal winter conditions allow for cost-effective storage since ambient temperatures are below base temperature and very little cooling is required (Winkler et al. 2018). Storage facilities could estimate costs associated with decreasing winter days by analyzing previous storage cost data for their winter periods. It is important to note that the impacts on refrigeration machinery associated with both winter decrease and SDD increase are not mutually exclusive. Prolonged SDD accumulation may impact facility operations by causing higher thermal loads on machinery which may initiate frequent breakdowns (Saidur et al. 2002). Shorter winters may also mean that machinery must work longer, and this increased running time will increase costs and may also contribute to premature breakdown or repair costs. (Jaglom et al. 2014)al., 2014).

4.3 Uncertainties and future work

Some uncertainty sources of this analysis must be considered when interpreting the projected changes in storage conditions. Definitions for the winter-start and winter-end dates can be altered based upon typical weather conditions for each region. A 0.25% change in SDD accumulation was required for 14 days to determine the beginning and end of winter subperiod. For simplicity, each region was given the same definition for winter period. Changes in this 0.25% definition can alter the number of winter days for each region and could allow for more localized planning based on geographical warm and cold spells. Additionally, our investigation was only interested in heat accumulation and its effect on storage conditions. Humidity regulation and controlled atmosphere are two additional energy consuming processes in cold storage that can be directly affected by temperature. These two processes may be affected by climate change, but they were not explored during this study. Furthermore, we used a specific range of storage dates for each crop (Table 2.2). If climate change alters planting or harvesting dates, then storage dates will be subsequently altered. Storage period shifts are likely in the future and should be continually monitored for more accurate changes in local cold storage conditions. Lastly, higher storage base temperatures can greatly decrease the energy demands required for crop storage. Current storage base temperatures for specific crops may be too low and increasing the base temperature could decrease costs associated with storage. The USDA reported the optimal storage base temperature for shelled peanuts should be 10°C for 10 months (USDA 2016). This contrasts to a recent study that identified that shelled peanuts can be stored at 13 °C for 1 year (Butts et al. 2017). This 3°C change can have large impacts on daily costs of storage and may allow commodities to be stored for a longer period at lower costs. Therefore, additional research must be conducted to ensure that current storage base temperatures are optimal for crop longevity, quality maintenance, and low cost storage.

Uncertainty is also inherent when assessing the future impacts of climate change and interpretation of ensembles must be conducted carefully (Winkler 2016). In our analyses, we employed 20 GCMs with two RCPs to create our ensemble of climate projections. Some GCMs predict much higher SDD accumulation values than other GCMs, but ensemble averages allow for a better interpretation of potential outcomes. It is important to note that the magnitude of projected changes in SDD accumulation is larger for RCP8.5 than RCP4.5. When utilized correctly, these ensembles allow for farmers, storage operators, and policy makers to plan ahead for future climate scenarios by understanding potential storage condition changes. Logistic planning for worst-case scenarios allows for potential extreme climate scenarios to have a lesser impact on facility infrastructure. Short-term climate adaptations may simply require more advanced refrigeration systems, but long-term adaptations may require significant planning and investment in new infrastructure.

5. Conclusion

This study shows that climate change will cause an increase in SDD accumulation and a decrease in length of winter subperiod in all U.S. regions. The aforementioned changes can reduce food availability within each region if postharvest losses become substantial. For future SDD accumulation, Northeast and Northwest apples stored at 1°C are expected to be affected most by climate change. For SDD percentage changes, Upper Midwest potatoes stored at 12.8°C and dropped to 8°C and Ohio Valley tomatoes stored at 14.4°C will be impacted the most. Upper Midwest potatoes stored at 12.8°C and dropped to 8°C will experience much shorter winter subperiods than they are accustomed. And Southeast region peanuts stored at 13°C will experience the largest percentage decrease in winter subperiod. In future climate scenarios, Upper Midwest region potatoes may be the most impacted crop due to higher SDD percentage increases and shorter winter lengths when compared to their historical reference period. While climate projections are uncertain, with inclusion of multiple GCMs the uncertainty can be quantified. This study details the role of global warming on cold storage conditions, which until recently have previously been largely ignored. Cold storage impact assessments for various crops should become routine when considering potential climate change scenarios.

Table 2.1 Highest grossing hub crop by region for cold storage analysis. Monetary value is the sum of the highest grossing hub crop for all states within each region. 2017 USDA NASS survey reports were used to calculate cumulative monetary value.

Climate Region	Crop Chosen	Cumulative Monetary Value
Southeast	Peanuts	$1,338,961,000.00
South	Peanuts	$291,447,000.00
Southwest	Lettuce	$566,773,000.00
West	Grapes	$5,793,217,000.00
Northwest	Apples	$2,430,353,000.00
Northern Rockies and Plains	Potatoes	$380,465,000.00
Upper Midwest	Potatoes	$674,209,000.00
Ohio Valley	Tomatoes	$167,492,000.00
Northeast	Apples	$577,356,000.00

Table 2.2 Crop identification, storage facility location, city coordinates, typical planting and harvesting dates, crop storage dates, and base temperature for crop storage analysis.

Region	Crop/ Variety	Regional Distributor	County, City, State	City Latitude and Longitude	Typical Planting and Harvesting Dates	Crop Storage Date(s) and Base Temp (C°)	Expected storage life (months)
Southeast	Peanut/ Runner	Birdsong Peanuts	Mitchell County Camila, GA	31.2313° N 84.2105° W	Planting Begin April 16; Most Active April 25-May 25; End June 6 Harvesting Begin Sept. 4; Most Active Sept. 22-Oct. 22; End Nov. 1	Start- 11/01 End - 6/30 13° C (Butts et al. 2017)	9
South	Peanut/ Runner	Golden Peanut Company	Gaines County Seminole, TX	32.7190° N 102.6449° W	Planting Begin May 7; Most Active May 29-June 31; End July 18 Harvesting Begin Sept. 7; Most Active Oct. 10-Nov. 22; End Dec. 20	Start- 12/01 End - 7/31 13° C (Butts et al. 2017)	9

Table 2.2 (continued)

Southwest	Head Lettuce/ Iceberg	Tanimura & Antle	Yuma County Yuma, AZ	32.6927° N 114.6277° W	Planting Begin Sept. 1; End Jan. 31 Harvesting Begin Nov. 1; Most Active Dec. 1-Mar.31; End April 30	Fall Start- 12/01 End - 12/31 Spring Start- 4/15 End - 5/15 2° C (Kerns et al. 1999)	0.5-1
West	Grape/ Table Grape	Hronis, Inc.	Kern County Delano, CA	35.7688° N 119.2471° W	Planting Begin N/A; Most Active N/A; End N/A Harvesting Begin July 10; Most Active N/A; End Oct. 15	Start- 10/01 End - 12/31 0° C (USDA, 2016)	3
Northwest	Apple/ Gala	Yakima Fruit & Cold Storage	Yakima County Wapato, WA	46.4476° N 120.4203° W	Planting Begin N/A; Most Active N/A; End N/A Harvesting Begin August; Most Active N/A; End Early Nov.	Start- 9/01 End - 6/30 1° C (USDA, 2016)	10-12

Table 2.2 (continued)

Northern Rockies and Plains	Potato/ Russet Burbank	Hoverson Farms	Grand Forks County Larimore, ND	47.9067° N 97.6268° W	Planting Begin May 15; Most Active N/A; End June 5 Harvesting Begin Sept. 1; Most Active N/A; End Late Oct.	Start- 9/01 End - 6/30 12.78° C drop down to 8.8° C (USDA, 2016)	10-12
Upper Midwest	Potato/ Hodag	Heartland Farms	Portage County Almond, WI	44.2589° N 89.4071° W	Planting Begin Early May; Most Active N/A; End Early June Harvesting Begin Early Sept.; Most Active N/A; End Mid October	Start - 9/01 End - 6/30 12.78° C drop down to 8° C (USDA, 2016)	10-12
Ohio Valley	Tomato Red Beefsteak	Mastronardi Produce	Auglaize County Wapakoneta, OH	40.5678° N 84.1936° W	Planting Begin July; Most Active N/A; End August Harvesting Begin Sept. 1; Most Active N/A; End May 31	Start- 9/01 End - 6/30 14.4° C (USDA, 2016)	1

Table 2.2 (continued)

Northeast	Apple MacIntosh	Fowler Brothers Inc.	Wayne County Wolcott, NY	43.2206° N 76.8150° W	Planting Begin N/A; Most Active N/A; End N/A Harvesting Begin Sept. 1; Most Active N/A; End Early Nov.	Start- 9/01 End - 6/30 1° C (USDA, 2016)	10-12

Table 2.3 GCMs derived from CMIP5 climate models to develop ensemble of downscaled projections for RCP4.5 and RCP8.5.

Number	Model Name	Model Country	Model Agency
1	bcc-csm1-1	China	Beijing Climate Center, China Meteorological Administration
2	bcc-csm1-1-m	China	Beijing Climate Center, China Meteorological Administration
3	BNU-ESM	China	College of Global Change and Earth System Science, Beijing Normal University
4	CanESM2	Canada	Canadian Centre for Climate Modeling and Analysis
5	CCSM4	USA	National Center of Atmospheric Research
6	CNRM-CM5	France	National Centre of Meteorological Research
7	CSIRO-Mk3-6-0	Australia	Commonwealth Scientific and Industrial Research Organization/Queensland Climate Change Centre of Excellence, Australia
8	GFDL-ESM2M	USA	NOAA Geophysical Fluid Dynamics Laboratory
9	GFDL-ESM2G	USA	NOAA Geophysical Fluid Dynamics Laboratory
10	HadGEM2-ES	United Kingdom	Met Office Hadley Center
11	HadGEM2-CC	United Kingdom	Met Office Hadley Center
12	inmcm4	Russia	Institute for Numerical Mathematics
13	IPSL-CM5A-LR	France	Institut Pierre Simon Laplace
14	IPSL-CM5A-MR	France	Institut Pierre Simon Laplace
15	IPSL-CM5B-LR	France	Institut Pierre Simon Laplace
16	MIROC5	Japan	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies,and Japan Agency for Marine-Earth Science and Technology
17	MIROC-ESM	Japan	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
18	MIROC-ESM-CHEM	Japan	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
19	MRI-CGCM3	Japan	Meteorological Research Institute
20	NorESM1-M	Norway	Norwegian Climate Center

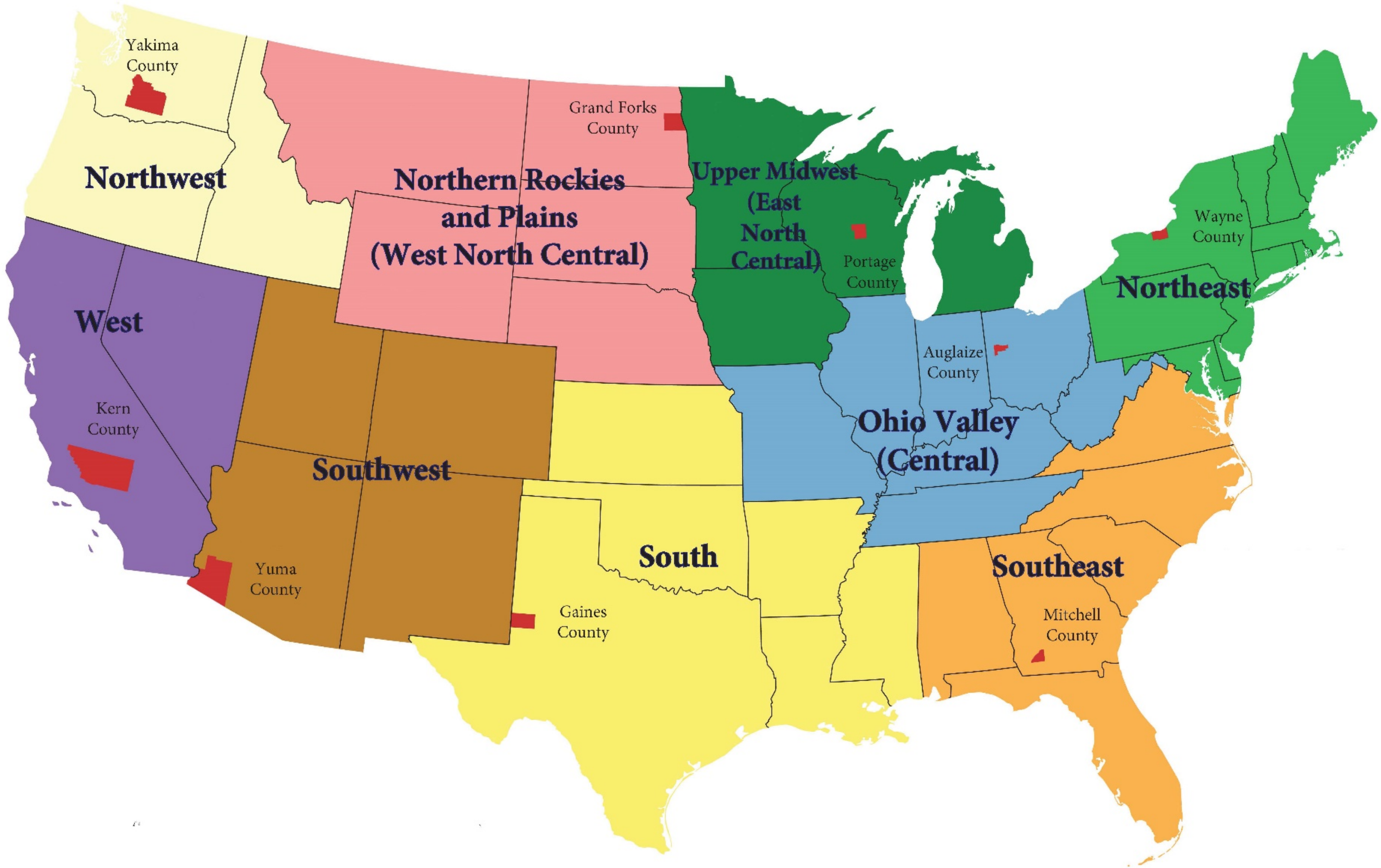

Figure 2.1 Nine climate regions in the CONUS. We identified county regions (red-colored) of highest production for the highest grossing crop requiring cold storage. This map is adapted from Karl and Koss (1984).

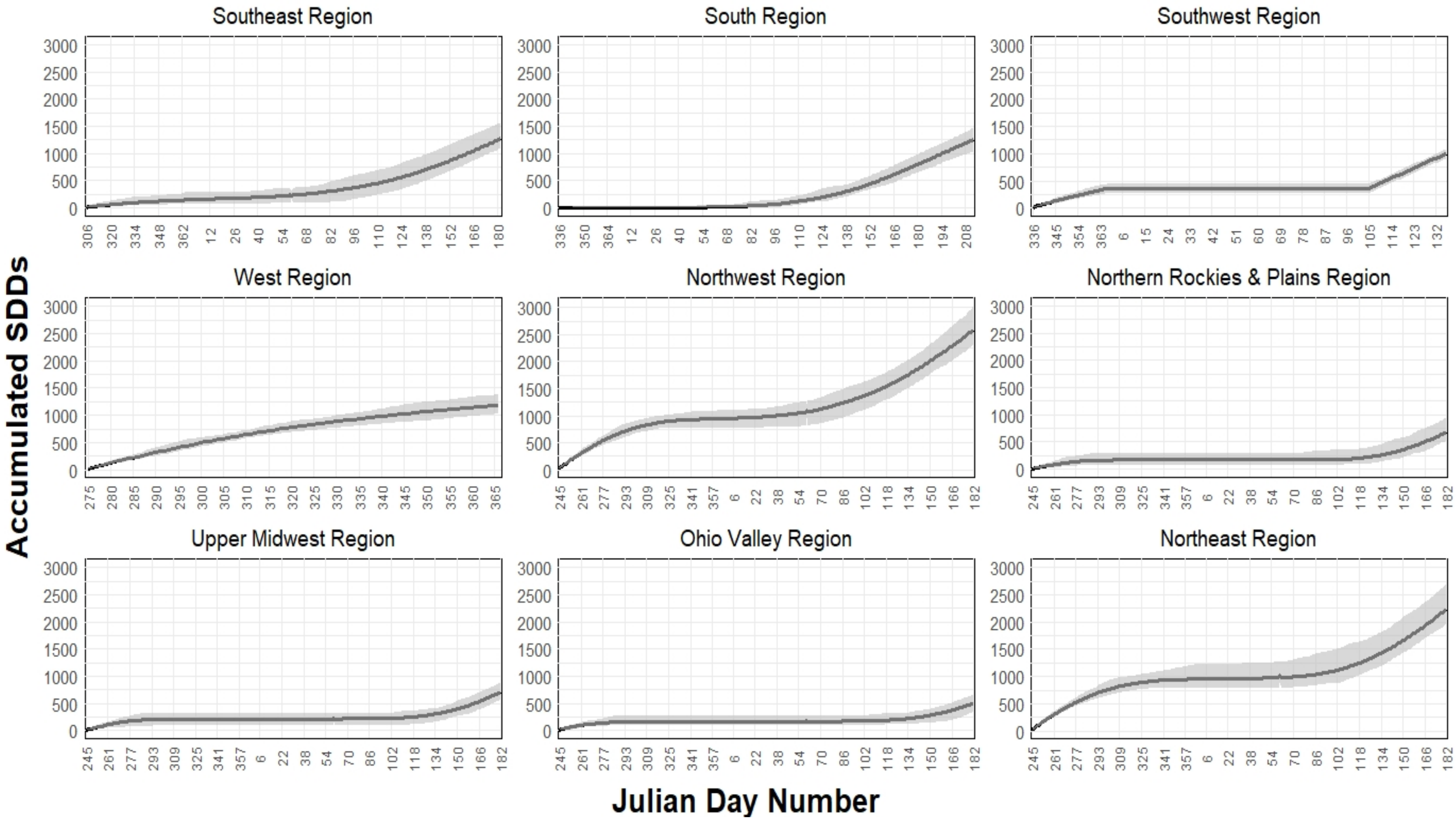

Figure 2.2 Maximum, minimum, and mean daily accumulation of storage degree days (SDDs) during the storage season of each region for 1979-2019 (historical reference period). The first Julian day for each region represents the typical first day of storage for that particular crop. The daily SDDs were smoothed using a 7-day moving average to minimize day-to-day fluctuations.

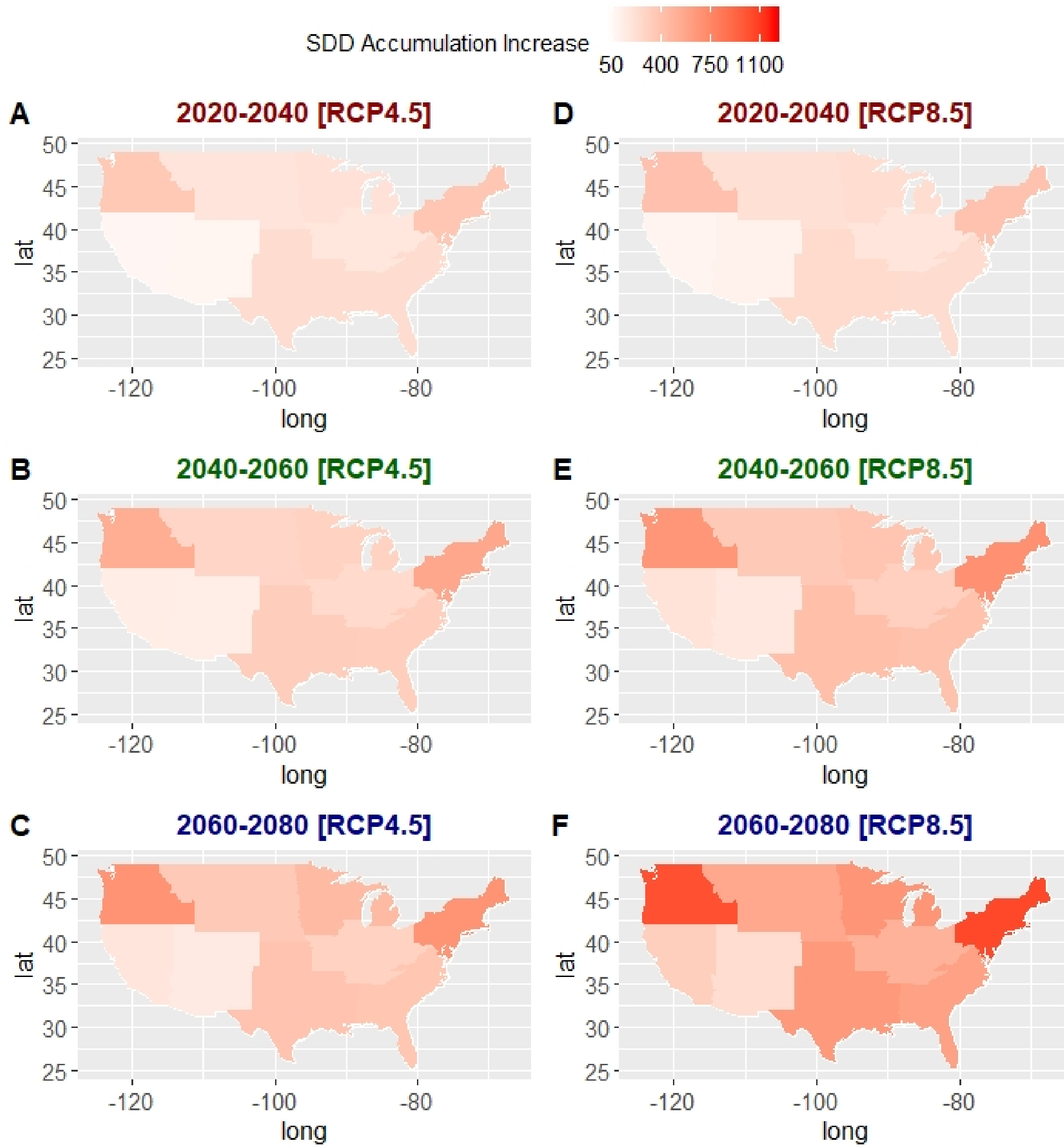

Figure 2.3 Projected SDD accumulation by region in the early, mid-, and late-century time slice for RCP4.5 (A,B,C) and RCP8.5(D,E,F). Final projected value(s) for SDD accumulation were averaged over the 20 GCMs on the final day of storage for each specific region. Highest increases in SDD accumulation are displayed in dark red.

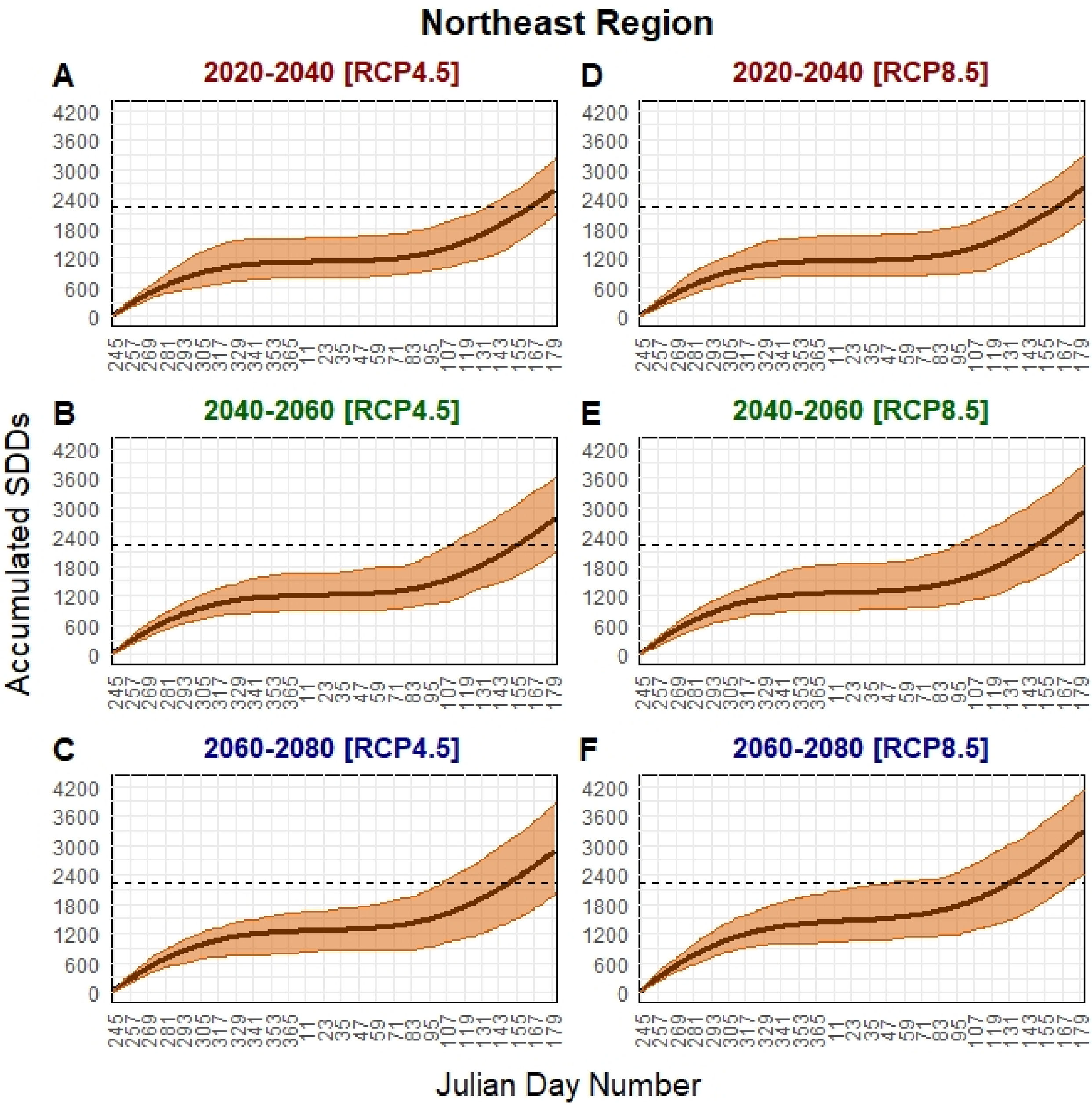

Figure 2.4 Projected SDD accumulation during the storage period (Sept. 1 – Jun. 30) for Northeast region (apples) for RCP4.5 (A,B,C) and RCP8.5 (D,E,F). Projected SDD accumulation for maximum and minimum GCM values are displayed in the red ribbon, and the mean of all GCMs is represented by the dark red line. Historical mean SDD accumulation on final day of storage (Jun. 30) is represented by the horizontal dashed line.

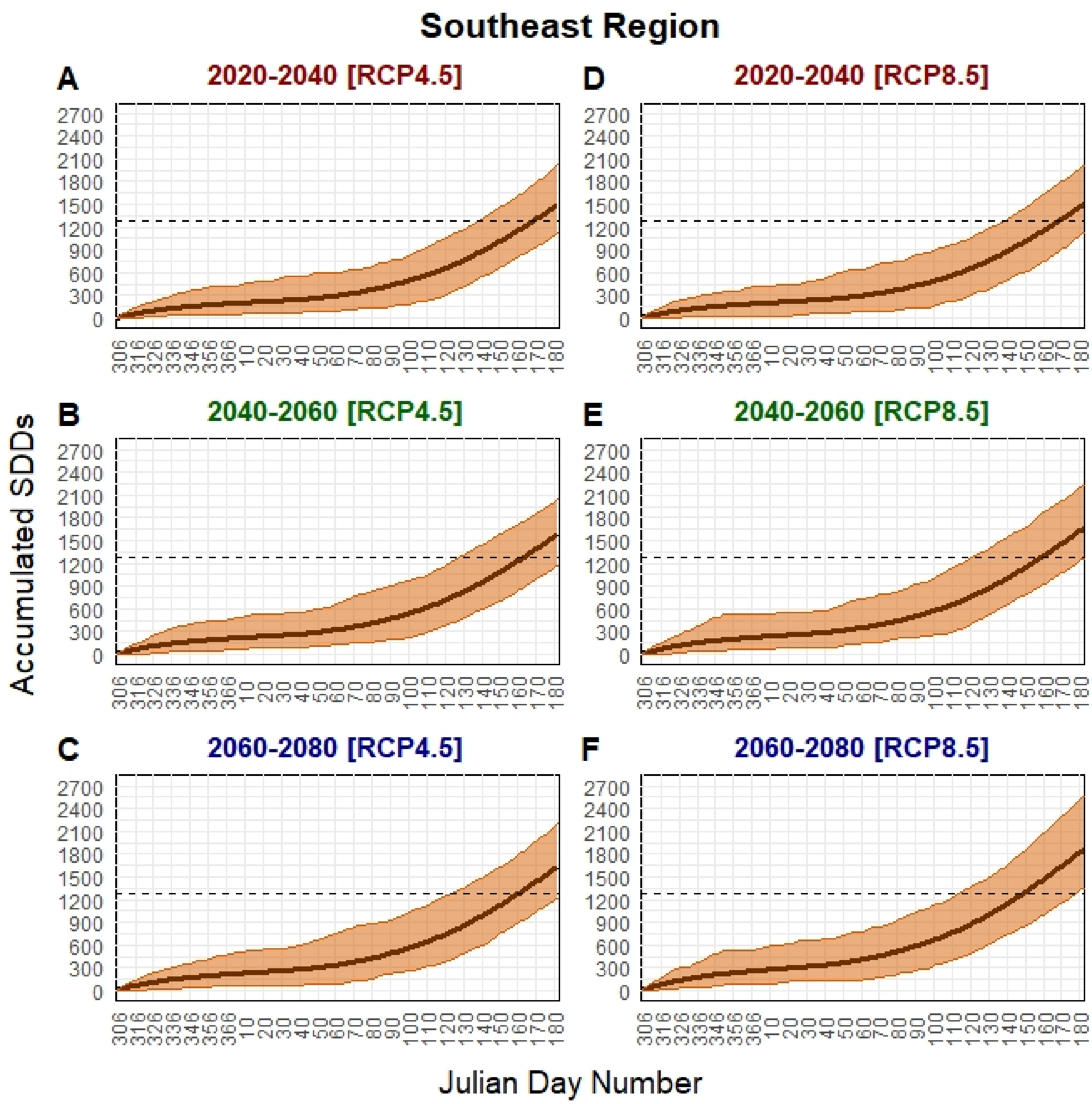

Figure 2.5 Projected SDD accumulation during the storage period (Nov. 1 – Jun. 30) for peanuts in the Southeast region for RCP4.5 (A,B,C) and RCP8.5 (D,E,F). Projected SDD accumulation for maximum and minimum GCM values are displayed in the red ribbon, and the mean of all GCMs is represented by the dark red line. Historical mean SDD accumulation on final day of storage (Jun. 30) is represented by the horizontal dashed line.

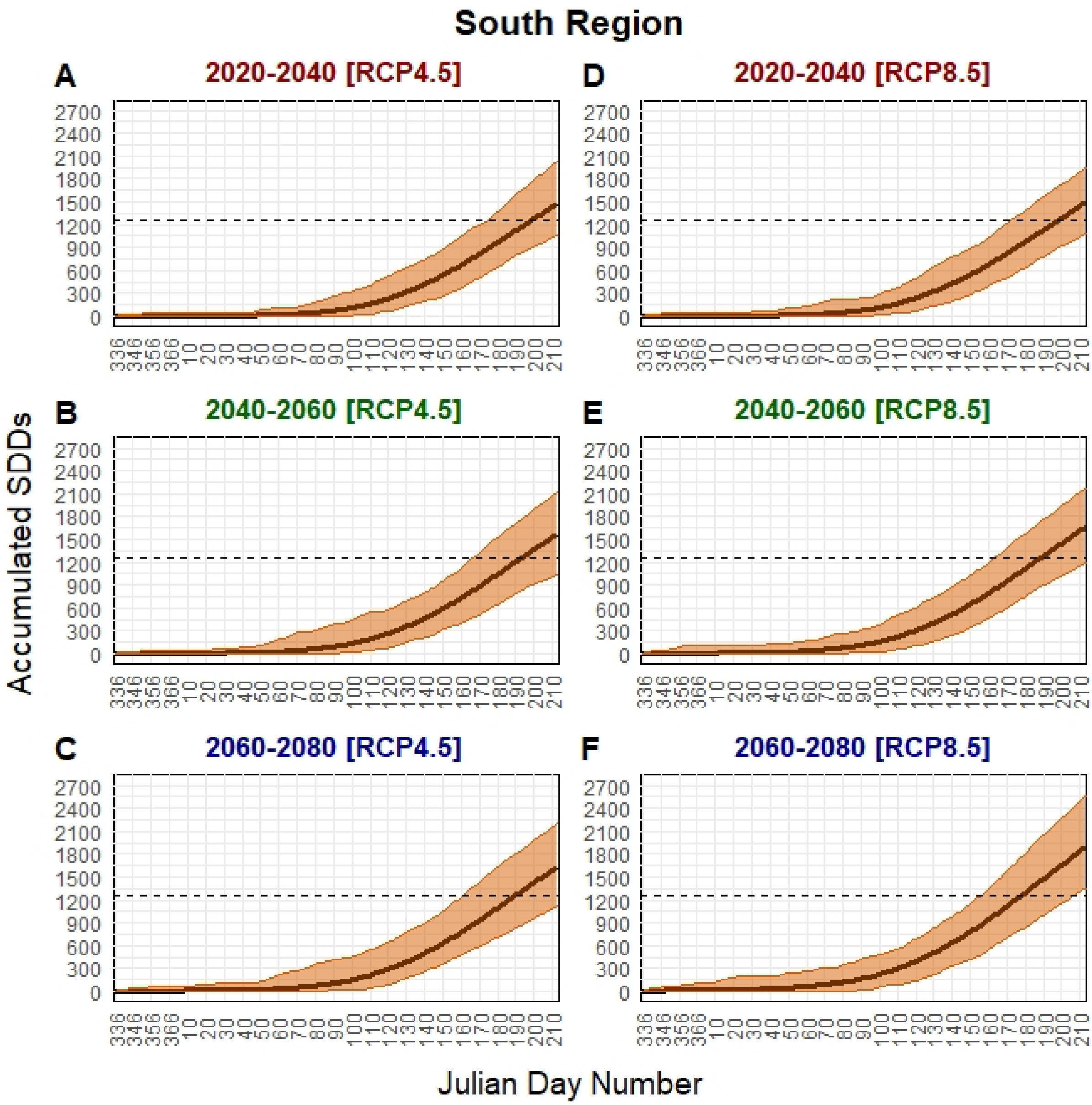

Figure 2.6 Projected SDD accumulation during the storage period (Dec. 1 – Jul. 31) for peanuts in the South region for RCP4.5 (A,B,C) and RCP8.5 (D,E,F). Projected SDD accumulation for maximum and minimum GCM values are displayed in the red ribbon, and the mean of all GCMs is represented by the dark red line. Historical mean SDD accumulation on final day of storage (Jul. 31) is represented by the horizontal dashed line.

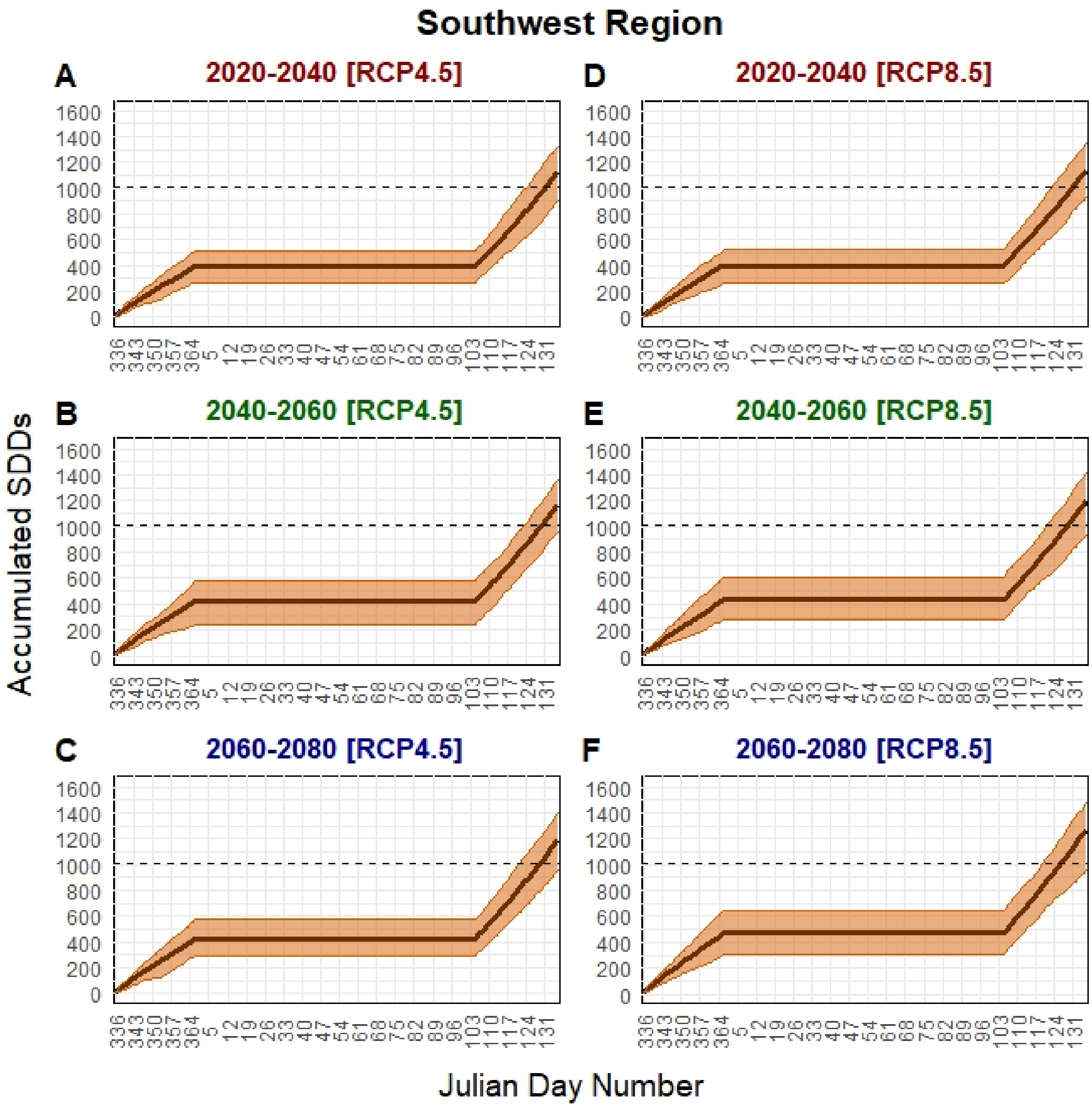

Figure 2.7 Projected SDD accumulation during the storage period (Dec. 1 – Dec. 31 & Apr. 15 – May 15) for lettuce in the Southwest region for RCP4.5 (A,B,C) and RCP8.5 (D,E,F). No storage occurs between Jan. 1 – Apr. 14. Projected SDD accumulation for maximum and minimum GCM values are displayed in the red ribbon, and the mean of all GCMs is represented by the dark red line. Historical mean SDD accumulation on final day of storage (May 15) is represented by the horizontal dashed line.

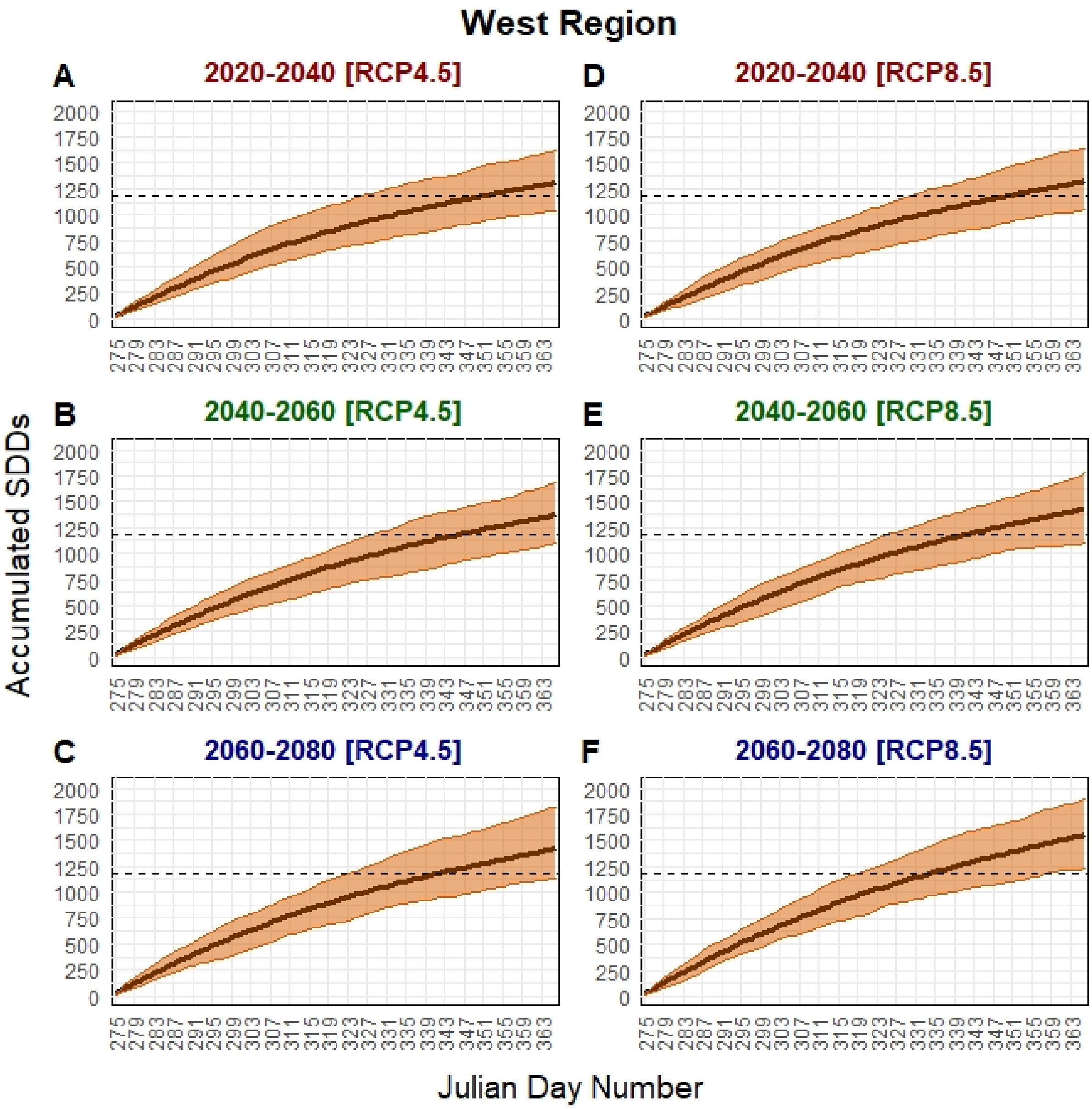

Figure 2.8 Projected SDD accumulation during the storage period (Oct. 1 – Dec. 31) for grapes in the West region for RCP4.5 (A,B,C) and RCP8.5 (D,E,F). Projected SDD accumulation for maximum and minimum GCM values are displayed in the red ribbon, and the mean of all GCMs is represented by the dark red line. Historical mean SDD accumulation on final day of storage (Jul. 31) is represented by the horizontal dashed line.

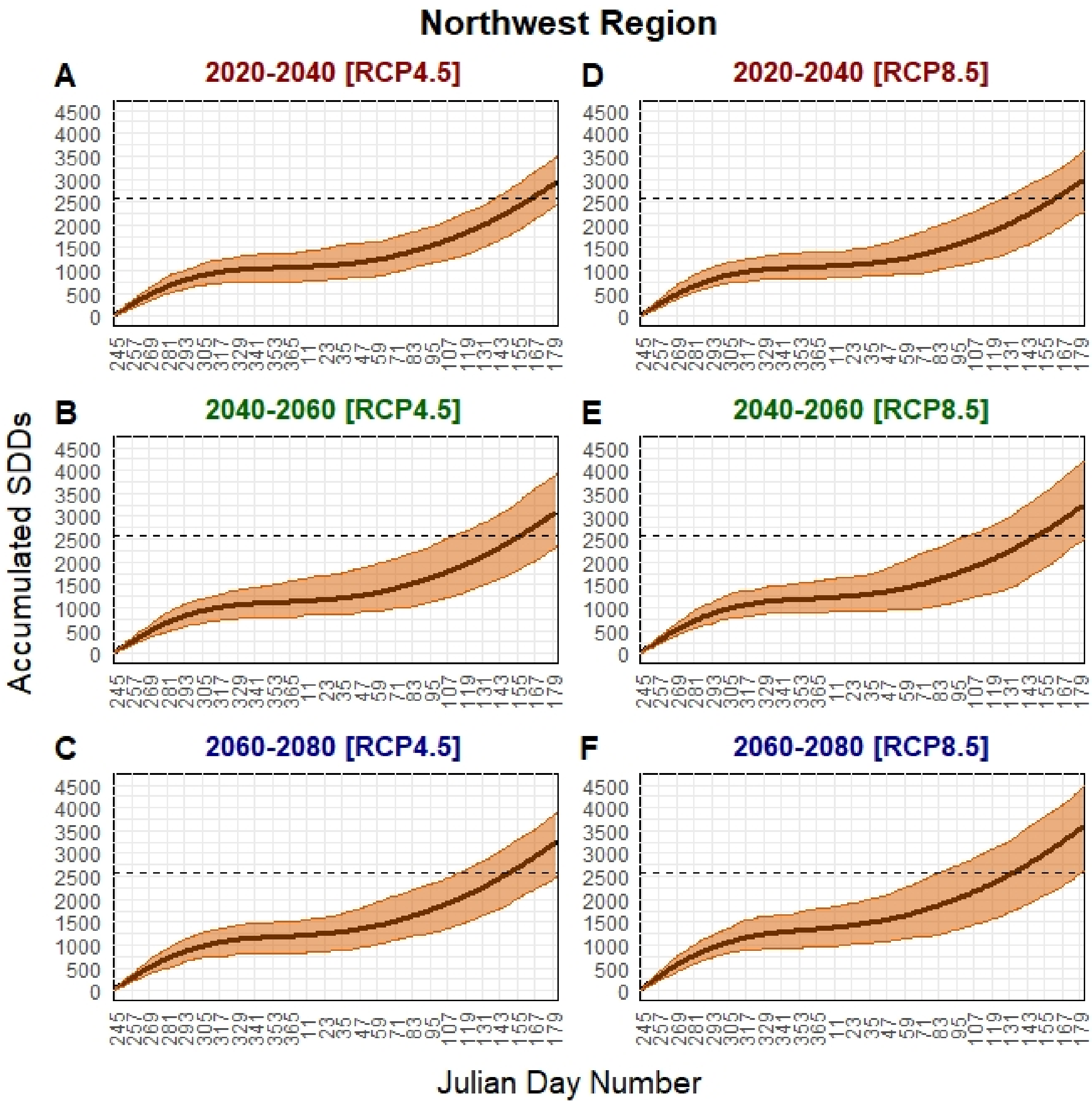

Figure 2.9 Projected SDD accumulation during the storage period (Sept. 1 – Jun. 30) for apples in the Northwest region for RCP4.5 (A,B,C) and RCP8.5 (D,E,F). Projected SDD accumulation for maximum and minimum GCM values are displayed in the red ribbon, and the mean of all GCMs is represented by the dark red line. Historical mean SDD accumulation on final day of storage (Jun. 30) is represented by the horizontal dashed line.

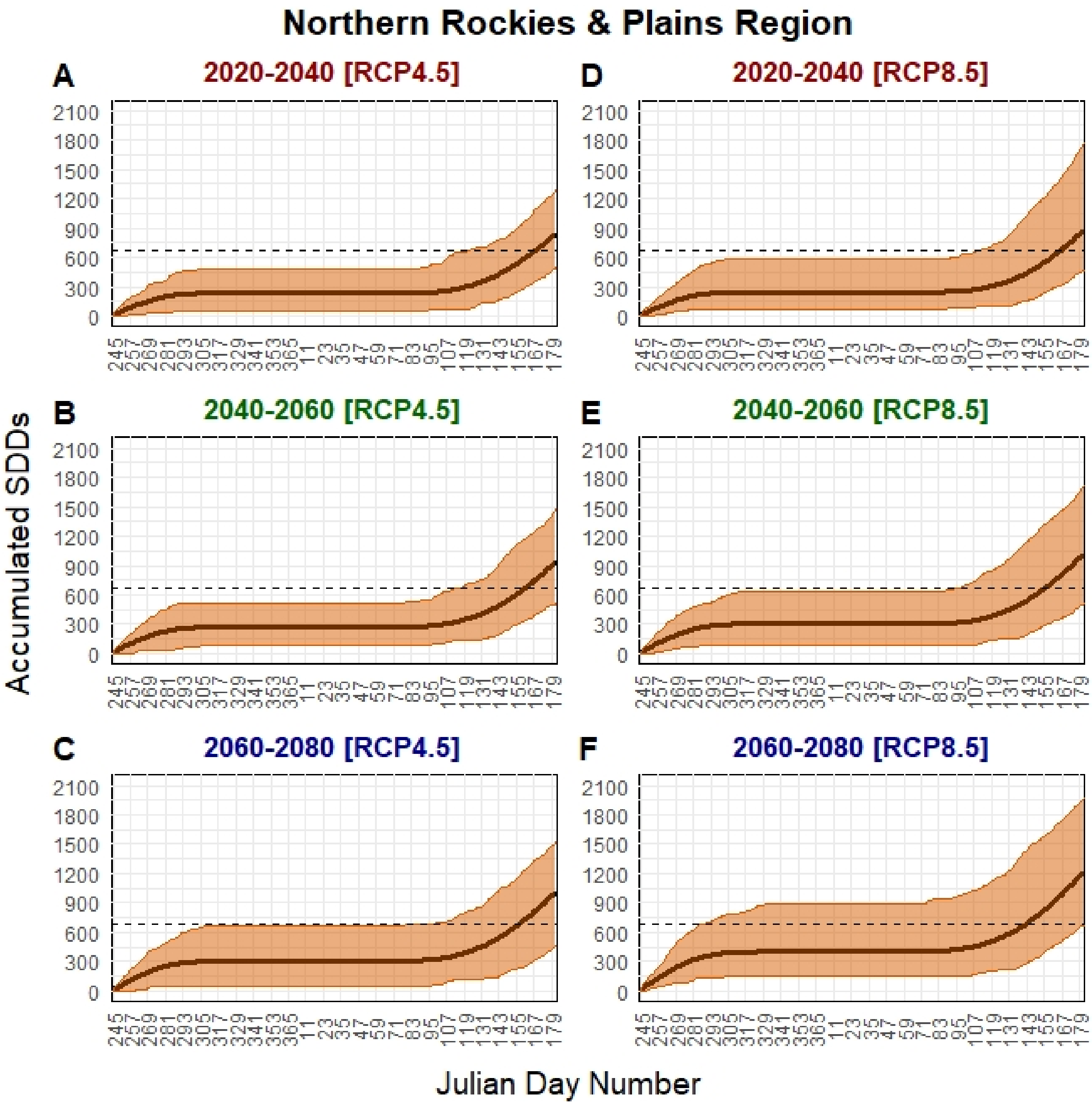

Figure 2.10 Projected SDD accumulation during the storage period (Sept. 1 – Jun. 30) for potatoes in the Northern Rockies & Plains region for RCP4.5 (A,B,C) and RCP8.5 (D,E,F). Projected SDD accumulation for maximum and minimum GCM values are displayed in the red ribbon, and the mean of all GCMs is represented by the dark red line. Historical mean SDD accumulation on final day of storage (Jun. 30) is represented by the horizontal dashed line.

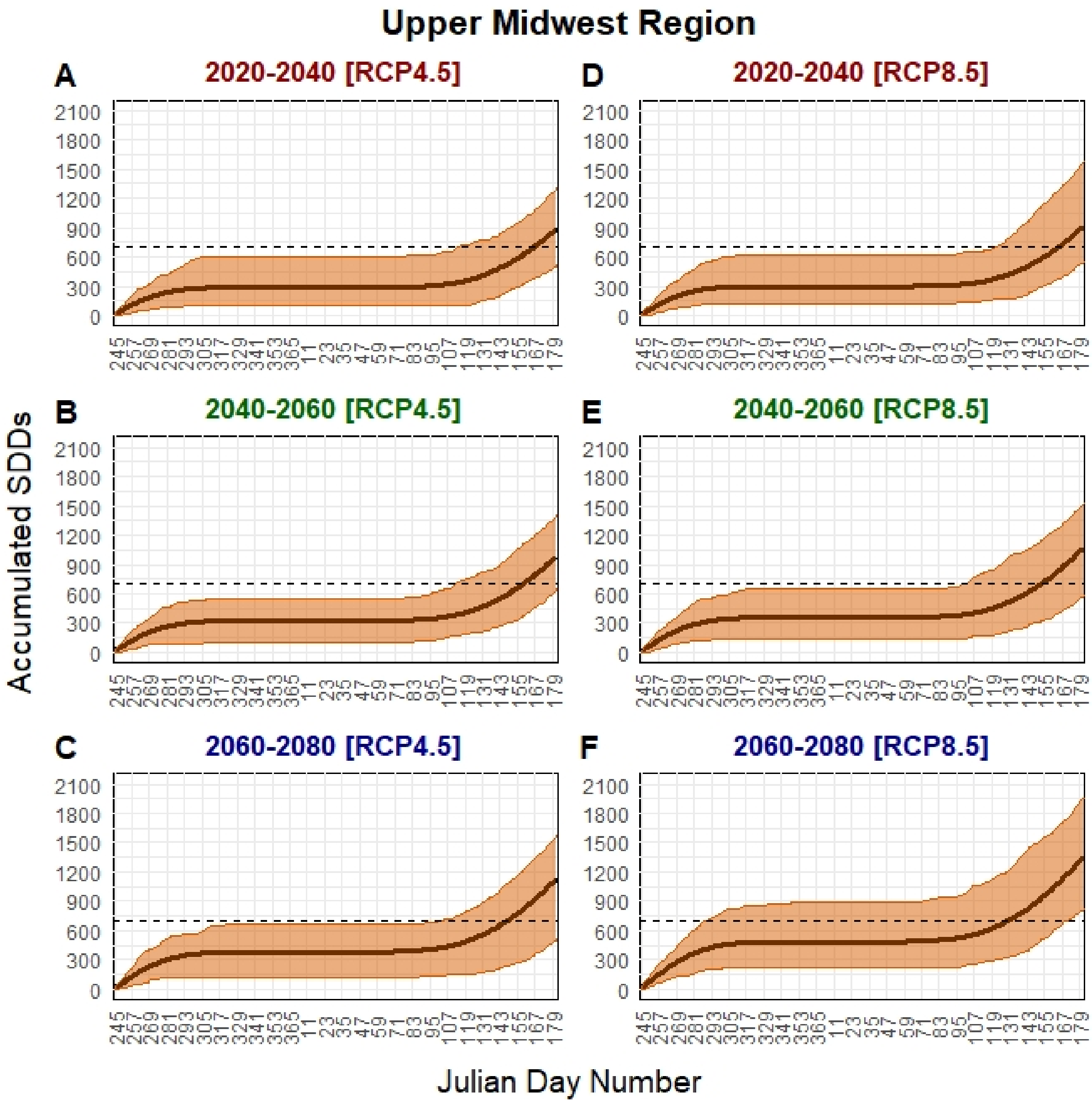

Figure 2.11 Projected SDD accumulation during the storage period (Sept. 1 – Jun. 30) for potatoes in the Upper Midwest region for RCP4.5 (A,B,C) and RCP8.5 (D,E,F). Projected SDD accumulation for maximum and minimum GCM values are displayed in the red ribbon, and the mean of all GCMs is represented by the dark red line. Historical mean SDD accumulation on final day of storage (Jun. 30) is represented by the horizontal dashed line.

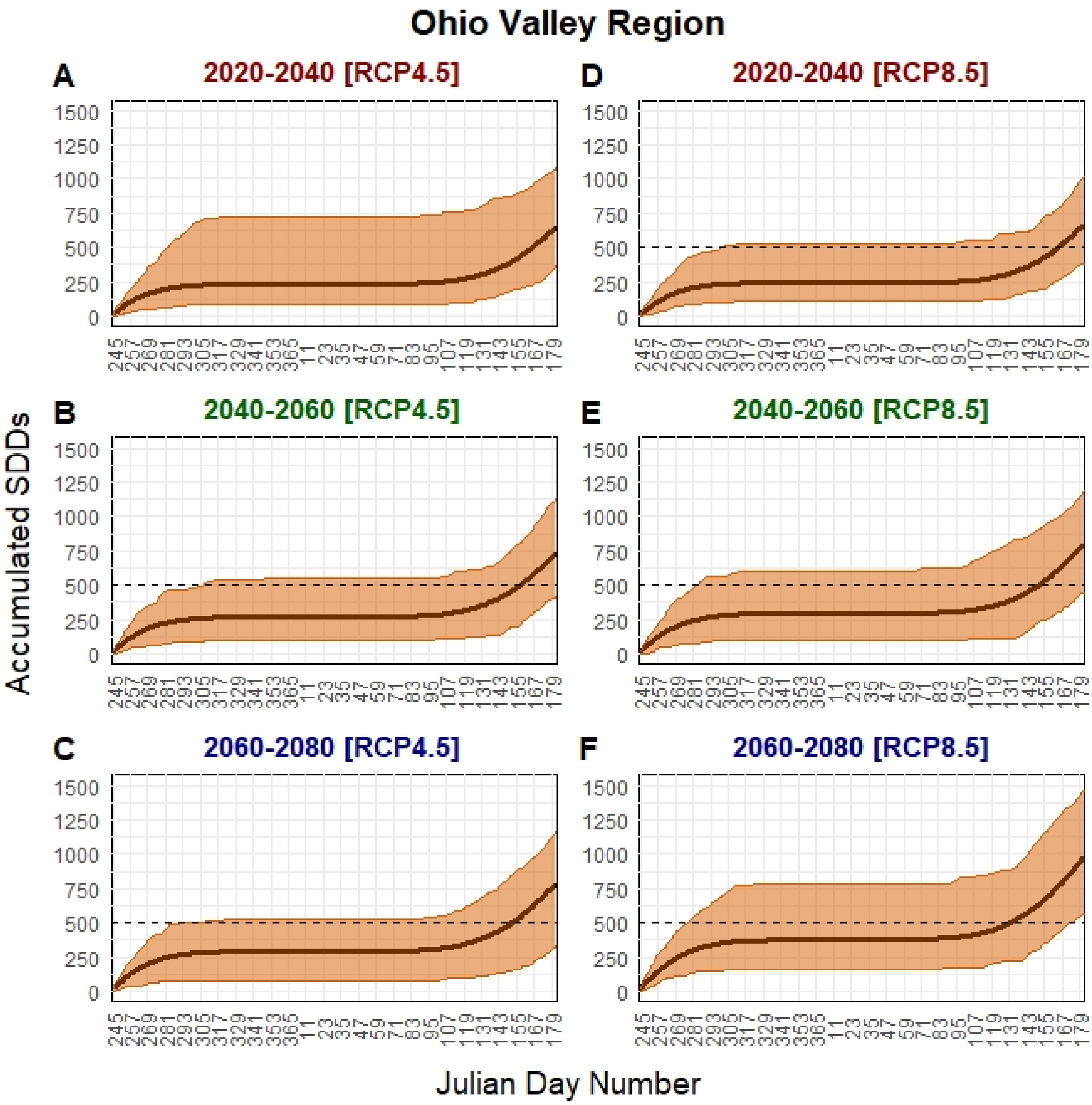

Figure 2.12 Projected SDD accumulation during the storage period (Sept. 1 – Jun. 30) for tomatoes in the Ohio Valley region for RCP4.5 (A,B,C) and RCP8.5 (D,E,F). Projected SDD accumulation for maximum and minimum GCM values are displayed in the red ribbon, and the mean of all GCMs is represented by the dark red line. Historical mean SDD accumulation on final day of storage (Jun. 30) is represented by the horizontal dashed line.

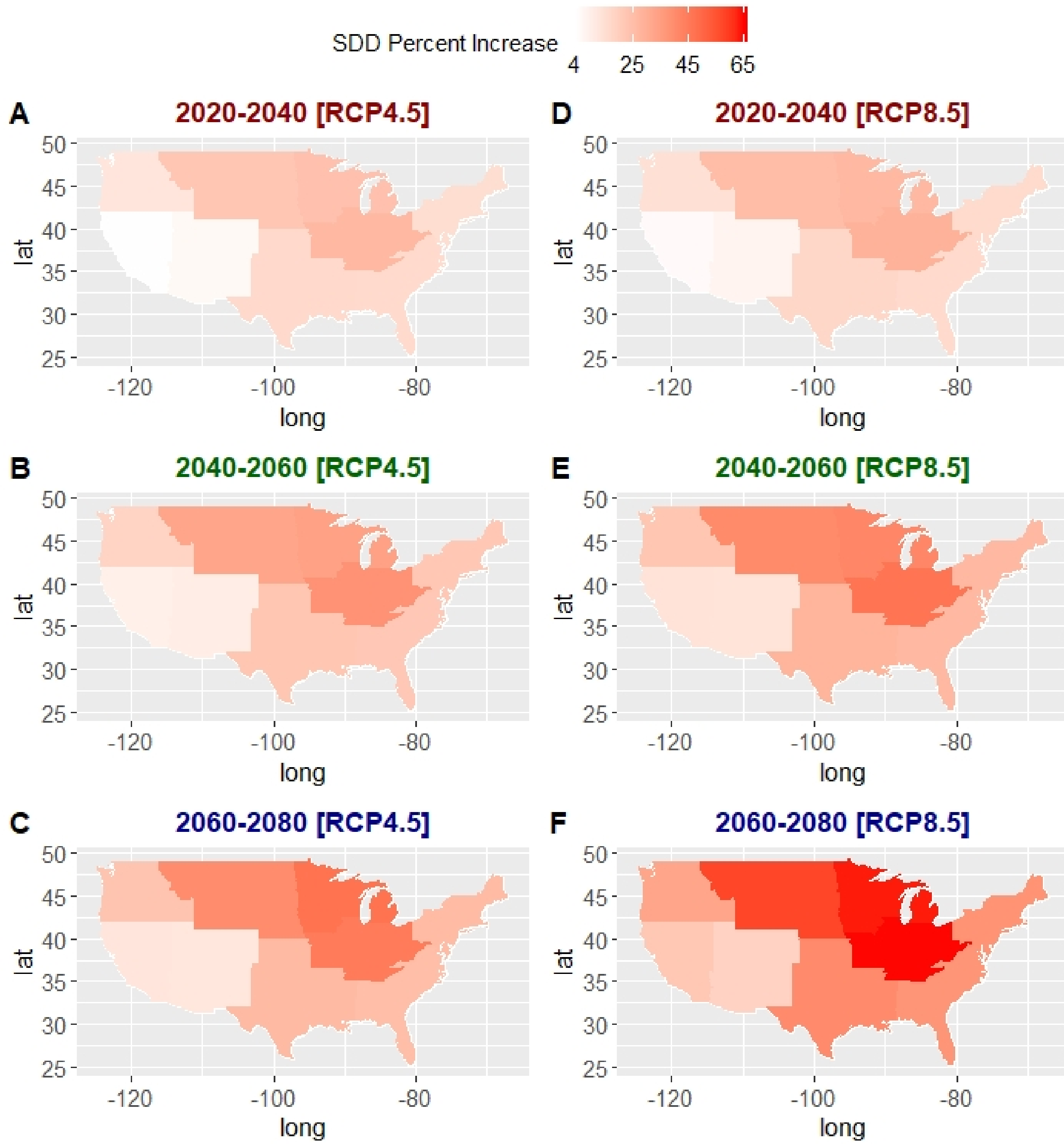

Figure 2.13 Projected SDD accumulation percentage increase by region in the early-, mid-, and late-century time slice for RCP4.5 (A,B,C) and RCP8.5(D,E,F). Final projected value(s) for SDD percentage change were averaged over the 20 GCMs on the final day of storage for each specific region. Highest increases in SDD percentage are displayed in dark red.

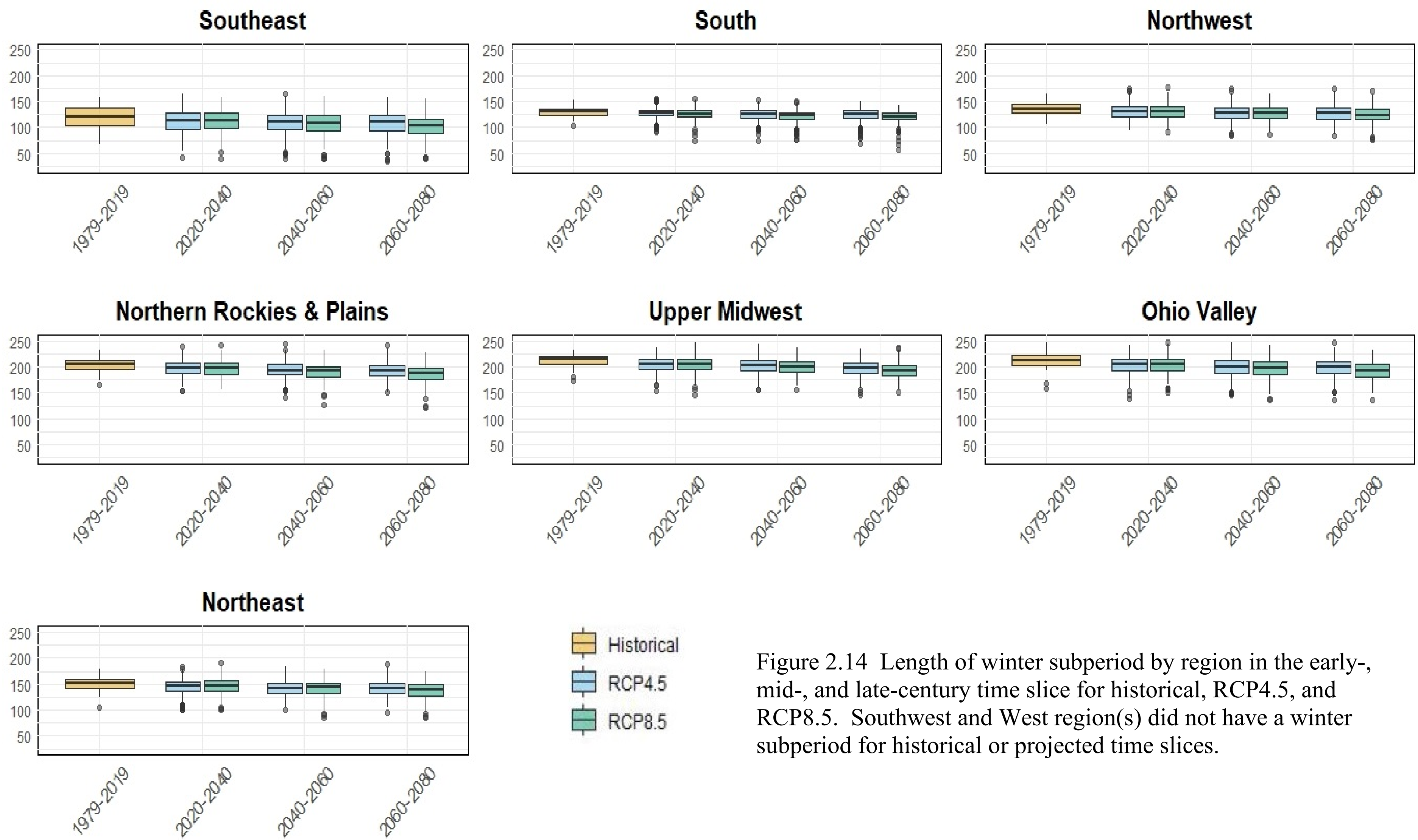

Figure 2.14 Length of winter subperiod by region in the early-, mid-, and late-century time slice for historical, RCP4.5, and RCP8.5. Southwest and West region(s) did not have a winter subperiod for historical or projected time slices.

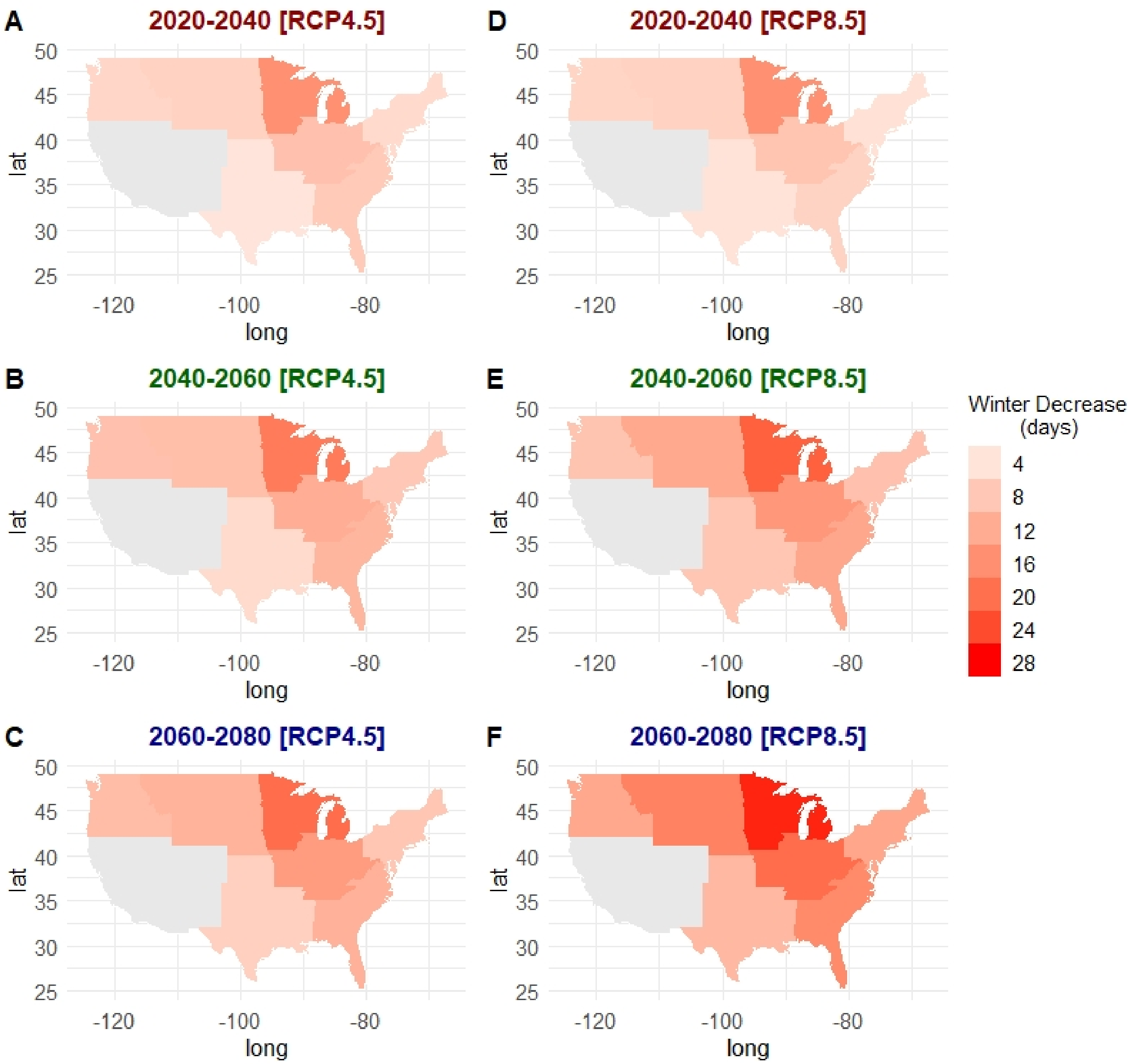

Figure 2.15 Projected decrease in length of winter subperiod by region in the early-, mid-, and late-century time slice for RCP4.5 (A,B,C) and RCP8.5(D,E,F). Highest decreases in winter length are displayed in dark red. Southwest and West regions did not have a winter period and are displayed in gray.

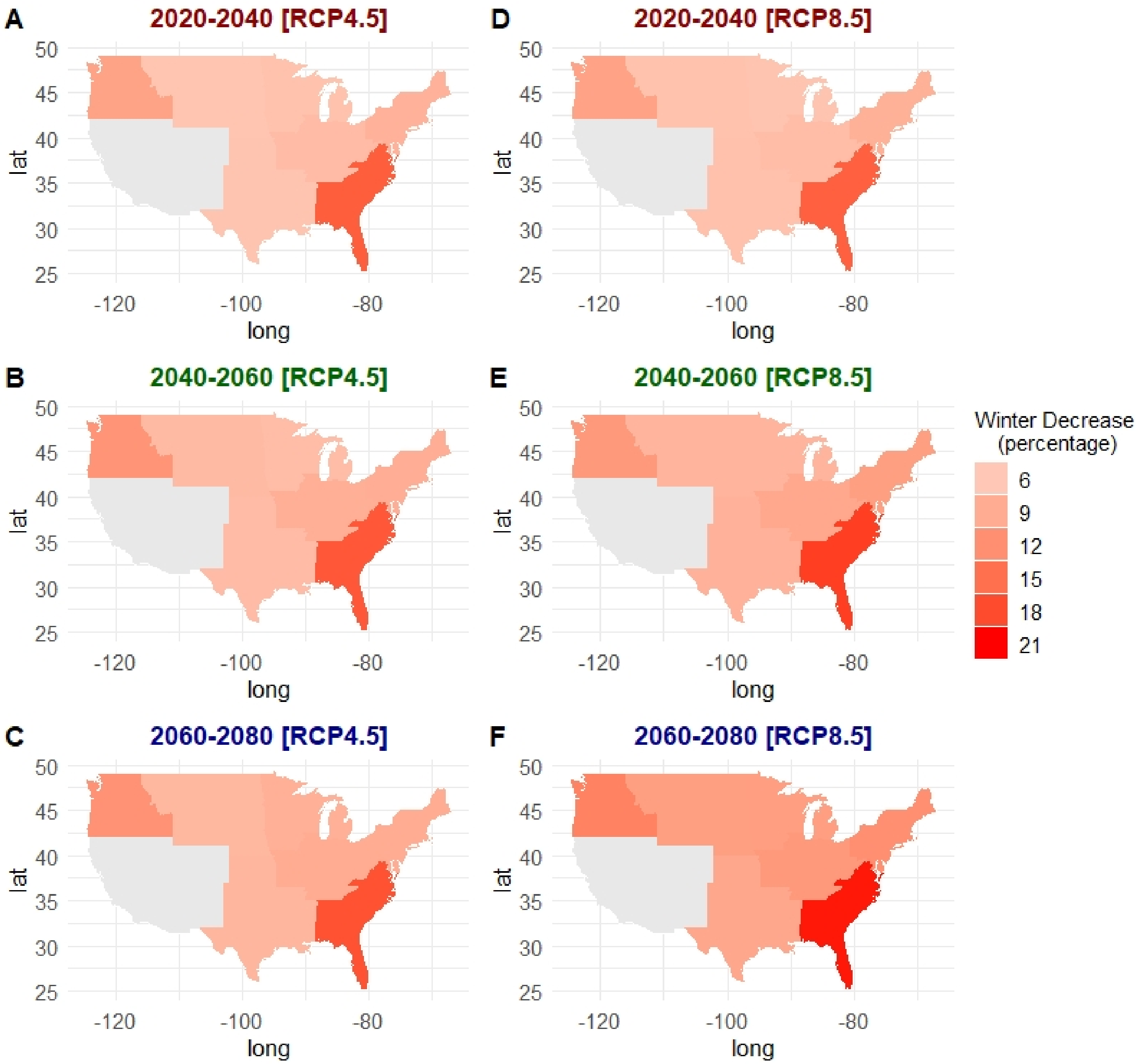

Figure 2.16 Projected percentage decrease in length of winter by region in the early-, mid-, and late-century time slice for RCP4.5 (A,B,C) and RCP8.5(D,E,F). Highest decreases in winter percentage change are displayed in dark red. Southwest and West regions did not have a winter period and are displayed in gray.

Chapter 3
Work Summary and Future Prospectives

1. Introduction

Our research has shown that climate change will greatly impact agricultural storage across the United States by increasing SDD requirements and reducing the length of the winter subperiod. These respective increases and decreases will require additional energy consumption to continue operating machinery at base temperatures; therefore, storage costs will be higher in the future if regional temperatures increase. Different U.S. regions will be affected at varying rates, but all regions will be affected regardless of RCP model (RCP4.5 or RCP8.5). Projected GCMs within each RCP model have ranges of uncertainty that do not allow for exact predictions, but these uncertainties can be minimized by using observed data and incorporation of correlating environmental variables (e.g., solar radiation, temperature, wind speed, cloud cover, etc.). In this chapter, we will discuss some observations found in chapter 1 and how this research can be improved or broadened to benefit additional stakeholders and agriculturalists to fight future food insecurity.

1.1 Climate Change and Future Impacts on Cold Storage

Food insecurity is a worldwide struggle and the United States is no exception with a 2018 report estimating that 11.1 percent of households were food insecure (USDA 2019). Food insecurity in the U.S. is not as prevalent as other developing countries, but food insecurity still exists. Availability or cost of products may inhibit some individuals from purchasing food, but costs can be lowered in the marketplace through increased yields, decreased postharvest losses, and decreased storage costs. Climate change can affect more than just commercial storage electrical costs, it can also affect their ability to continue operations due to crop shortage or failure. Cold storage has been shown to be integral to supply production and global trade (Simon-Elorz and Inchusta 1999), but we only identified how increasing temperatures will affect storage facility SDD accumulation and the length of the winter subperiod. We now examine additional factors that may affect U.S. agroeconomics that may contribute to future food insecurity.

Cold storage of crops in commercial facilities is one portion of the cold chain crop transport system that is used to preserve crop values for the marketplace. Our crop storage analysis was focused only on temperature and its effects on SDD accumulation and length of the winter subperiod – but temperature is not the only factor affecting crop preservation or energy consumption. Different crops require various storage conditions for inhibition of microbes, relative humidity (RH), oxygen, CO2, and nitrogen (USDA 2016). Changes in the aforementioned storage conditions were not analyzed in this study, but future research can identify the impacts on agriculture caused by climate change. Increasing temperatures can increase the microbial activity in what is commonly known as the Q10 temperature coefficient (Xiao 1999). Increased microbial activity, through infestation or disease, can occur pre- or postharvest and may contribute to premature degradation and a loss of crop value. If infestation and disease affect crop yields and there is less to store, consumer costs will substantially increase due to less products on the market. Further loss of crop values can occur in cold storage and exacerbate food insecurity in the U.S.

Higher ambient temperatures would not greatly affect crop values in cold storage, but rather decrease crop yields and increase storage costs.

1.2 Humidity

In our research, all crops in storage required RH conditions somewhere between 55-100% and all storage temperatures were lower than 14.4°C (Table 3.1). The quicker a crop meets the storage base temperature and RH requirements, the longer the crop can be stored before degradation occurs. Changes in outside RH or inside RH can have immediate effects on crop quality. Outside high RH can contribute to the production of mycotoxins by fungi with can infect crops in the field or crops in route to storage facilities (Bradford et al. 2018). Psychrometric charts are useful when displaying relationships that exist between temperature, RH, water vapor pressure, and air pressure (Figure 3.1); therefore, one can examine how temperature and pressure may affect future RH maintenance in a storage environment (Camuffo 2019). High RH is necessary in cold storage facilities to prevent water loss and shriveling in fruits and vegetable. Since cold storage rooms are much colder than adjacent non-cold rooms, any air that enters from opening of the doors will increase RH. Increasing ambient temperatures will lead to higher moisture in the cold room; therefore, reducing RH may be necessary in future climate scenarios. Future research can investigate how quickly cold rooms meet minimum acceptable storage standards based upon both temperature and RH. Pressure differences by altitude can also directly affect RH rates. Warehouse RH can be influenced by temperature distribution in the room, air exchange rates, packing materials used, surface are of the refrigeration evaporator coil, or temperature difference between coil and air (Paull 1998). If temperatures continues to rise, larger gradients will exist between the coil and the air and this will result in a loss of efficiency. Additional costs for RH maintenance may also arise based upon pressure differences and these must be investigated on an individual altitude basis. Since barometric pressure affects RH, pressure differences around the country can influence how quickly a refrigerated area meets acceptable temperature and RH rates. Future research must identify how efficiently machinery is operating under varying pressure, RH, and temperature differences.

1.2 Yield Changes

Cold storage facilities require commodities to be stored to remain operational. Although this statement seems juvenile, climate change has the ability to negatively impacts yields so that not enough crops make it to cold storage. Research has previously identified that climate change can reduce yields of grapes (Lobell et al. 2006), apples (Singh et al. 2016), tomatoes (Datta 2013), peanuts (Pearson et al. 1997), and potatoes (Raymundo et al. 2018), but not all studies have been conducted with the U.S. Additional research must now be conducted on both yield and storage condition changes specific to the U.S. for crops to understand the full impact of climate change on crop values. Our research has already identified projected changes in storage conditions, so addition of changes in yields would create a more impactful study. Future forecasting can identify impacted changes in crop planting dates, harvest dates, crop yields, and then crop storage to understand the regional agricultural impacts caused by climate change. In the future, it is probable that reduced yields and increased storage costs could devastate day-to-day operations in cold storage by either not having enough crops to store or storage costs remaining too high.

1.3 Hydrology Changes

Climate-related impacts are not limited to elevated temperatures, but may also include changes in hydrology or extreme weather events that hinder or prevent adequate storage of crops (Gautam 2018; Lesk et al. 2016). Hydrological changes can create instances of drought or flooding which can greatly reduce crop yields. In order to mitigate these extreme weather events, climate smart farming may need to be incorporated with climate smart landscapes (Scherr et al. 2012). These climate smart landscapes allows agriculturalists to adapt by changing surface runoff procedures, diversifying land use, and managing land use interactions to achieve positive impacts. So now, farmers and agriculturalists must think climate smart about both crops and land use due to climate uncertainties in the future. The climatic changes are influenced greatly by multidecadal shifts in weather patterns that can include the Atlantic Multidecadal Oscillation (AMO), Pacific Decadal Oscillation (PDO), or El Nino-Southern Oscillation (ENSO) (Legler et al. 1999; Levine et al. 2017; Mantua and Hare 2002). Understanding these weather patterns allows researchers to identify the changes in hydrology and predict future changes. Temperature, hydrology, and extreme weather event changes can be researched simultaneously to identify the degree of correlation and potential impacts on yield and storage.

1.4 Differing Crop Varieties and Rotations

Climate-smart agriculture encourages resiliency and adaptive strategies when preparing for climate change. Our research was focused on a single crop variety in each region, but additional research can identify other regional hub crops that require cold storage and how they are impacted by climate change. It is possible that one crop variety is better suited for drought resistance or higher temperatures; therefore, identification of the least impacted crop variety would be very beneficial to farmers. Farmers can begin to diversity their fields and incorporate that specific variety into their rotations. Monocultures in agriculture will become more risky in the future due to crop failures and avoidance of monocultures will be critical in the fight against food insecurity (Altieri et al. 2015). By diversifying crops, farmers will attain a higher resilience in the event that future climate anomalies destroy specific crop varieties. Brankatsch and Finkbeiner (2017) investigated how certain crop rotations for the production of bread, milk, and biofuels are able to reduce the product carbon footprint. Their research can be utilized worldwide and may lead to the investigation of new rotations that can further reduce carbon emissions. Future climate impact research can identify both successful crop rotations and varieties that produce high yields under stressful climate events. (Brankatschk and Finkbeiner 2017)

1.5 CMIP6 Climate Data (Arndt 2015)

Without changing our research project on cold storage conditions within the U.S., we could now employ a new set of climate data that may improve impact forecasting. CMIP Phase 6 (CMIP6) is now freely available for climate research and includes 33 MIPs and a newly updated Coupled Climate-Carbon Cycle Model Intercomparison Project (C4MIP) specifically for carbon feedbacks (Eyring et al. 2016; Jones et al. 2016). C4MIP would be most beneficial for GHG impact studies, but the added benefit of CMIP6 is the incorporation of 32 other endorsed MIPs that can assist scientists with their own specific research interests and priorities (e.g., aerosols, lan0use, volcanic forcings, sea ice, etc.). This allows for the rapid analyzation of multiple impacts on the same land type since MIP datasets exists for numerous environmental variables. CMIP5 left scientific gaps that are will now be addressed in CMIP6 experiments. Climate researchers now seek to understand 1) How does the Earth system respond to changes in forcing?, 2) What are the origins and consequence of systematic model biases?, 3) How can we assess future climate changes given climate variability, predictability, and uncertainties in scenarios? CMIP6 now includes 4 new RCP scenarios and 4 updated RCP scenarios for a total of 8 possible RCP radiative forcing scenarios. These new and updated RCPs give scientists a wider selection of simulations for regional and global planning. Mitigation planning can now occur with CMIP6 because scientists can compare “high CO2 emissions” against “no CO2 emissions". Future climate forecasting should become more reliant on CMIP6 due to its continued growth and incorporation of environmental variables and feedbacks.

Conclusion

Increasing the resiliency and strength of agricultural systems is necessary in the U.S. to prevent food insecurity. Agricultural impact studies can now incorporate numerous environmental variables when assessing changes in crop yield, storage, or land use changes based upon future climate scenarios. CMIP6 will become increasingly important in an effort to reduce both uncertainty and to provide a wider range of possible climate outcomes. Future research in agricultural engineering will also be important to reduce energy consumption and the carbon footprint. Climate-smart agriculture in conjunction with climate-smart land use may be able to offset future CO2 emissions, but this must be accomplished on a nationwide scale in order to be efficacious. Climate mitigation through reduced CO2 emissions can be greatly improved through cooperation between farmers, agriculturalists, scientists, and policymakers.

Table 3.1 Crop identification, typical planting and harvesting dates, crop storage dates, base temperature for crop storage, humidity requirements, and expected storage life for each climatically consistent region in the U.S.

Region	Crop/ Variety	Typical Planting and Harvesting Season Dates	Crop Storage Date(s) and Base Temp (C°)	Humidity (RH%)	Expected storage life (months)
Southeast	Peanut Runner	Planting Begin April 16 Most Active April 25 -May 25 End June 6 Harvesting Begin Sept. 4 Most Active Sept. 22- Oct. 22 End Nov. 1	Start - 11/01 End - 6/30 13° C (Butts et al. 2017)	55-70	9
South	Peanut Runner	Planting Begin May 7 Most Active May 29 - June 31 End July 18 Harvesting Begin Sept. 7 Most Active Oct. 10 - Nov 22 End Dec. 20	Start - 12/01 End - 7/31 13° C (Butts et al. 2017)	55-70	9
Southwest	Head Lettuce Iceberg	Planting Begin Sept. 1 End Jan. 31 Harvesting Begin Nov. 1 Most Active Dec. 1 - Mar. 31 End Apr. 30	Fall Start - 12/01 End - 12/31 Spring Start - 4/15 End - 5/15 2° C (Kerns et al. 1999)	>95	0.5-1

3.1(continued)

Region	Crop/ Variety	Typical Planting and Harvesting Season Dates	Crop Storage Date(s) and Base Temp (C°)	Humidity (RH%)	Expected storage life (months)
West	Grape Table Grape	Planting Begin N/A Most Active N/A End N/A Harvesting Begin - July 10 Most Active N/A End - Oct. 15	Start - 10/01 End - 12/31 0° C (USDA, 2016)	90-95	3
Northwest	Apple Gala	Planting Begin N/A Most Active N/A End N/A Harvesting Begin - August Most Active N/A End - Early Nov.	Start - 9/01 End - 6/30 1° C (USDA, 2016)	95	10-12
West North Central	Potato Russet Burbank	Planting Begin May 15 Most Active N/A End June 5 Harvesting Begin Sept. 1 Most Active N/A End Late Oct.	Start - 9/01 End - 6/30 12.78° C drop down to 8° C (USDA, 2016)	80-100	10-12

Table 3.1 (continued)

Region	Crop/ Variety	Typical Planting and Harvesting Season Dates	Crop Storage Date(s) and Base Temp (C°)	Humidity (RH%)	Expected storage life (months)
East North Central	Potato Hodag	Planting Begin Early May Most Active N/A End Early June Harvesting Begin Sept. Most Active N/A End Mid October	Start - 9/01 End - 6/30 12.78° C drop down to 8.8° C (USDA, 2016)	80-100	10-12
Central	Tomato Red Beefsteak	Planting Begin July Most Active N/A End August Harvesting Begin Sept. 1 Most Active N/A End May 31	Start - 9/01 End - 6/30 14.4° C (USDA, 2016)	85-95	1
Northeast	Apple MacIntosh	Planting Begin N/A Most Active N/A End N/A Harvesting Begin Sept. 1 Most Active N/A End Early Nov.	Start - 9/01 End - 6/30 1° C (USDA, 2016)	90	10-12

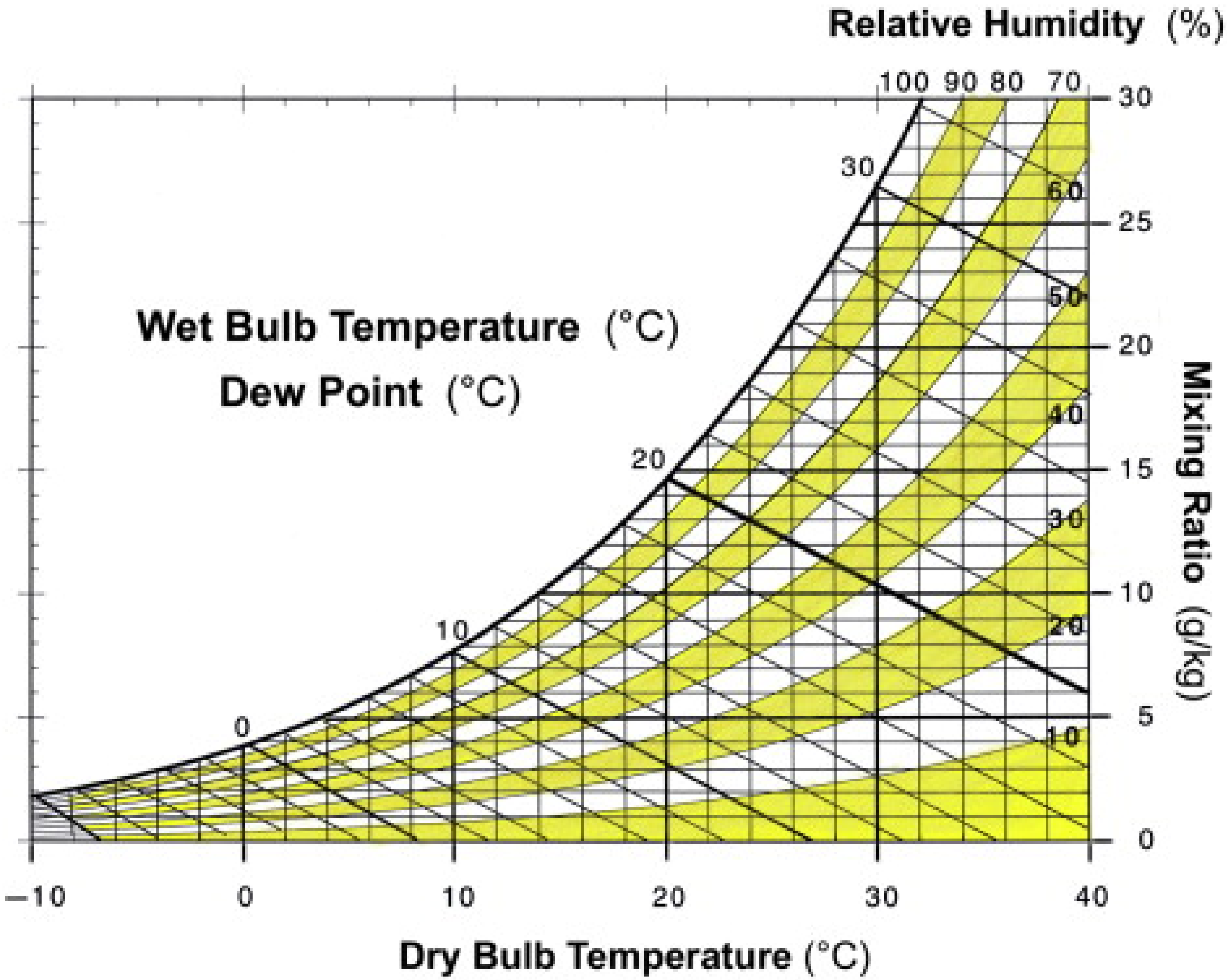

Figure 3.1 Psychrometric chart for calculation of relative humidity at 1 atm total pressure. Knowledge of any two parameters will allow for the calculation of all other parameters (e.g., knowledge of dew point and dry bulb temp will allow for calculation of relative humidity). Previous knowledge of atmospheric pressure must be known since each psychrometric chart is specific to a specific atmospheric pressure. Dario Camuffo, *The Psychrometric Chart*, 2014, website image, accessed 26 February, 2020, https://www.sciencedirect.com/topics/engineering/psychrometric-chart.

References

Abatzoglou JT (2013) Development of Gridded Surface Meteorological Data for Ecological Applications and Modelling. International Journal of Climatology 33:121-131.

Abatzoglou JT, Brown TJ (2012) A Comparison of Statistical Downscaling Methods Suited for Wildfire Applications. International Journal of Climatology 32:772-780.

Abatzoglou JT, Williams AP (2016) Impact of Anthropogenic Climate Change on Wildfire across Western Us Forests. Proceedings of the National Academy of Sciences 113:11770-11775.

Ackerly DD, et al (2010) The Geography of Climate Change: Implications for Conservation Biogeography. Diversity and Distributions 16:476-487.

Aggarwal PK, et al (2006) Infocrop: A Dynamic Simulation Model for the Assessment of Crop Yields, Losses Due to Pests, and Environmental Impact of Agro-Ecosystems in Tropical Environments. I. Model Description. Agricultural Systems 89:1-25.

Akinsanola AA, et al (2018) Evaluation of Rainfall Simulations over West Africa in Dynamically Downscaled Cmip5 Global Circulation Models. Theoretical and Applied Climatology:437-450.

Allen MR, et al (2009) Warming Caused by Cumulative Carbon Emissions Towards the Trillionth Tonne. Nature 458:1163-1169.

Altieri MA, et al (2015) Agroecology and the Design of Climate Change-Resilient Farming Systems. Agronomy for Sustainable Development 35:869-890.

Arndt D (2015) Climate Change Rule of Thumb: Cold "Things" Warming Faster Than Warm Things. CliamteWatch Magazine, Climate.gov.

Bajželj B, Richards K (2014) The Positive Feedback Loop between the Impacts of Climate Change and Agricultural Expansion and Relocation. Land 3:898-916.

Banger K (2015) Net Exchanges of Carbon Dioxide, Methane, and Nitrous Oxide between Terrestrial Ecosystems and the Stmmosphere in Tropical Asia During 1901-2010, Auburn University.

Barbero R, et al (2015) Climate Change Presents Increased Potential for Very Large Fires in the Contiguous United States. International Journal of Wildland Fire 24:892-899.

Bauer E, et al (2003) Assessing Climate Forcings of the Earth System for the Past Millennium. Geophysical Research Letters 30.

Bediako JA, et al (2009) Crop Storage Efficiency and Market Competitiveness: Case of Groundnut and Cowpea in Ghana. African Journal of Marketing Management 1:081-088.

Board TE (2019) The World Needed a Bang from the Madrid Climate Meeting. It Got a Whimper Instead. Los Angeles Times.

Bohl WH, Johnson SB (2010) Commercial Potato Production in North America.

Bradford KJ, et al (2018) The Dry Chain: Reducing Postharvest Losses and Improving Food Safety in Humid Climates. Trends in Food Science & Technology 71:84-93.

Brankatschk G, Finkbeiner M (2017) Crop Rotations and Crop Residues Are Relevant Parameters for Agricultural Carbon Footprints. Agronomy for Sustainable Development 37.

Bron IU, et al (2005) Temperature-Related Changes in Respiration and Q10 Coefficient of Guava. Science Agriculture 62:458-463.

Butts CL, et al (2017) Alternative Storage Environments for Shelled Peanuts. Peanut Science 44:111-123.

Cammarano D, Tian D (2018) The Effects of Projected Climate and Climate Extremes on a Winter and Summer Crop in the Southeast USA. Agricultural and Forest Meteorology 248:109-118.

Camuffo D (2019) Microclimate for Cultural Heritage: Measurement, Risk Assessment, Conservation, Restoration, and Maintenance of Indoor and Outdoor Monuments. Candice Janco, Amsterdam, Netherlands; Oxford, United Kingdom; Cambridge, United States.

Cardi T, Varshney R (2016) Cisgenesis and Genome Editing: Combining Concepts and Efforts for a Smarter Use of Genetic Resources in Crop Breeding. Plant Breeding 135:139-147.

Chin N, et al (2018) Assessing Potential Winter Weather Response to Climate Change and Implications for Tourism in the U.S. Great Lakes and Midwest. Journal of Hydrology: Regional Studies 19:42-56.

Clasen BM, et al (2016) Improving Cold Storage and Processing Traits in Potato through Targeted Gene Knockout. Plant Biotechnol J 14:169-176.

Colby SL, Ortman JM (2015) Projections of the Size and Composition of the U.S. Population: 2014 to 2060. Population Estimates and Projections. in Bureau USC (ed.).

Colombo RC, et al (2018) Postharvest Longevity of 'Brs Vitória' Seedless Grapes Subjected to Cold Storage and Acibenzolar-S-Methyl Application. Pesquisa Agropecuária Brasileira 53:809-814.

CSI (2016) Causes of Climate Change. http://www.ces.fau.edu/nasa/module-4/causes/sources-carbon-dioxide.php.

Datta S (2013) Impact of Climate Change in Indian Horticulture - a Review. International Journal of Science, Environment, and Technology 2:661-671.

EnergyTrust (2014) Cold Storage Facilities Energy Savings Guide. https://www.energytrust.org/wp-content/uploads/2016/12/ind_fs_guide_coldstorage.pdf.

EPA (2016) Causes of Climate Change. https://19january2017snapshot.epa.gov/climate-change-science/causes-climate-change_.html.

EPA (2017) Overview of Greenhouse Gases. https://www.epa.gov/ghgemissions/overview-greenhouse-gases.

Ertugrul M (2019) Future Forest Fire Danger Projections Using Global Circulation Models (Gcms) in Turkey. Fresenius Environmental Bulletin 28:3261-3269.

Eyring V, et al (2016) Overview of the Coupled Model Intercomparison Project Phase 6 (Cmip6) Experimental Design and Organization. Geoscientific Model Development 9:1937-1958.

FAO I, UNICEF, WFP, WHO (2019) The State of Food Security and Nutrition in the World 2019. Safeguarding against Economic Slowdowns and Downturns. in Nations U (ed.). FAO, Rome.

Fountain H (2019) Climate Change Is Accelrating, Bring World "Dangerously Close" to Irreversible Change. New York Times.

Fowler HJ, et al (2007) Linking Climate Change Modelling to Impacts Studies: Recent Advances in Downscaling Techniques for Hydrological Modelling. International Journal of Climatology 27:1547-1578.

Fuglie KO (1999) Economics of Potato Storage: Case Studies. Global Conference on Potato, New Delhi, India.

Fuhrer J (2003) Agroecosystem Responses to Combinations of Elevated Co2, Ozone, and Global Climate Change. Agriculture, Ecosystems & Environment 97:1-20.

Gautam S (2018) Climate Change Impacts on Hydrologic Components and Occurence of Drough in an Agricultural Watershed, University of Missouri.

Gibson B (2019) The Industrialized World Is Failing to Meet Paris Agreement Goals. The American Prospect, Inc.

Gordon K, Lewis M (2017) It's Time to Close the "Carbon Loophole". Wall Street Journal.

Hadley SW, et al (2006) Responses of Energy Use to Climate Change: A Climate Modeling Study. Geophysical Research Letters 33.

Harel D, et al (2013) Evaluation of Low Pressure Fogging System for Improving Crop Yield of Tomato (Lycopersicon Esculentum Mill.): Grown under Heat Stress Conditions. Agronomy 3:497-507.

Hayhoe K, et al (2010) Regional Climate Change Projections for Chicago and the Us Great Lakes. Journal of Great Lakes Research 36:7-21.

Hernández V, et al (2015) Impact of Shading on Tomato Yield and Quality Cultivated with Different N Doses under High Temperature Climate. Procedia Environmental Sciences 29:197-198.

Hristov AN, et al (2017) Climate Change Effects on Livestock in the Northeast Us and Strategies for Adaptation. Climatic Change 146:33-45.

IPCC (2014a) Climate Change 2014 Mitigation of Climate Change: Working Group Iii Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. in Edenhofer O, Pichs-Madruga R, Sokona Y, Farahani E, Kadner S, Seyboth K, Adler A, Baum I, Brunner S, Eickemeier P, Kriemann B, Savolainen J, Schlömer S, von Stechow C, Zwickel T, Minx JC (eds.).

IPCC (2014b) Climate Change 2014: Synthesis Report. Contribution of Working Groups I, Ii, and Ii to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. in Pachauri RK, Meyer LA (eds.). IPCC, Geneva, Switzerland, p. 151.

IPCC (2019) History of the Intergovernmental Panel on Climate Change. https://www.ipcc.ch/about/history/.

Jaglom WS, et al (2014) Assessment of Projected Temperature Impacts from Climate Change on the U.S. Electric Power Sector Using the Integrated Planning Model®. Energy Policy 73:524-539.

James SJ, James C (2010) The Food Cold-Chain and Climate Change. Food Research International 43:1944-1956.

Jones CD, et al (2016) C4mip – the Coupled Climate–Carbon Cycle Model Intercomparison Project: Experimental Protocol for Cmip6. Geoscientific Model Development 9:2853-2880.

Karl TR, Koss WJ (1984) Regional and National Monthly, Seasonal, and Annual Temperature Weighted by Area, 1895-1983. in Center NCD (ed.), Asheville, N.C.

Karmalkar AV, Bradley RS (2017) Consequences of Global Warming of 1.5 Degrees C and 2 Degrees C for Regional Temperature and Precipitation Changes in the Contiguous United States. PLoS One 12:e0168697.

Kerns DL, et al (1999) Guidelines for Head Lettuce Production in Arizona. University of Arizona.

Khanal B, Uprety D (2014) Effects of Storage Temperature on Post-Harvest of Potato. International Journal of Research 1:903-909.

Klos PZ, et al (2014) Extent of the Rain-Snow Transition Zone in the Western U.S. Under Historic and Projected Climate. Geophysical Research Letters 41:4560-4568.

Krishnakumar TD (2002) Design of Cold Storage for Fruits and Vegetables. in Initiative I-CTCR (ed.). ICAR-Central Tuber Crops Research Initiative, Trivandrum, Kerala.

Legler DM, et al (1999) Impact of Enso-Related Climate Anomalies on Crop Yields in the U.S. Climatic Change 42:351-375.

Lesk C, et al (2016) Influence of Extreme Weather Disasters on Global Crop Production. Nature 529:84-87.

Levine AFZ, et al (2017) The Impact of the Amo on Multidecadal Enso Variability. Geophysical Research Letters 44:3877-3886.

Lindsey R (2019) Climate Change: Atmospheric Carbon Dioxide. ClimateWatch, Climate.gov.

Lobell DB, et al (2006) Impacts of Future Climate Change on California Perennial Crop Yields: Model Projections with Climate and Crop Uncertainties. Agricultural and Forest Meteorology 141:208-218.

Lubin G (2016) 26 Maps That Show How Ethnic Groups Are Divided across America. https://www.businessinsider.com/maps-of-ancestry-groups-in-america-2013-9.

Luedeling E, et al (2011) Climate Change Affects Winter Chill for Temperate Fruit and Nut Trees. PLoS One 6:e20155.

Mantua NJ, Hare SR (2002) The Pacific Decadal Oscillation. Journal of Oceanography 58:35-44.

McFarland J, et al (2015) Impacts of Rising Air Temperatures and Emissions Mitigation on Electricity Demand and Supply in the United States: A Multi-Model Comparison. Climatic Change 131:111-125.

McGarvey JC, et al (2015) Carbon Storage in Old-Growth Forests of the Mid-Atlantic toward Better Understanding the Eastern Forest Carbon Sink. Ecology 96:311-317.

Montanari R (2008) Cold Chain Tracking: A Managerial Perspective. Trends in Food Science & Technology 19:425-431.

Morrison RM, et al (2019) Ag and Food Sectors of the Economy. January 15 2020 https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/ag-and-food-sectors-and-the-economy/#:~:targetText=Agriculture%2C%20food%2C%20and%20related%20industries,about%201%20percent%20of%20GDP.

Moss RH, et al (2010) The Next Generation of Scenarios for Climate Change Research and Assessment. Nature 463:747-756.

Mutegi CK, et al (2013) Effect of Storage Conditions on Quality and Aflatoxin Contamination of Peanuts (Arachis Hypogaea L.). International Journal of AgriScience 3:746-758.

NALC (2019) International Treaties and Agreements. https://nationalaglawcenter.org/overview/international-trade/#:~:targetText=Its%20implem.

Nations UNU (2016) Un Announces First-Ever Global Standard to Measure Food Loss and Waste. 2019 https://www.un.org/sustainabledevelopment/blog/2016/06/un-announces-first-ever-global-standard-to-measure-food-loss-and-waste/.

ND.gov (2019) Nd State Seed Department Contacts. March 07 2019 https://www.nd.gov/seed/.

Noorhosseini SA, et al (2018) Modeling the Impact of Climate Change on Peanut Production on the Basis of Increase 2 Degree C Temperature in Future Environmental Conditions of Guilan Province, Iran. International Journal of Agricultural Management and Development (IJAMAD) 8:257-273.

Parrish JT, Peterson F (1988) Wind Directions Predicted from Global Circulation Models and Wind Directions Determined from Eolian Sandstones of the Western United States - a Comparison. Sedimentary Geology 56:261-282.

Paull RE (1998) Effect of Temperature and Relative Humidity on Fresh Commodity Quality. Postharvest Biology and Technology 15:263-277.

Pearson S, et al (1997) A Validated Model to Predict the Effects of Environment on the Growth of Lettuce (Lactuca Sativa L.): Implications for Climate Change. Journal of Horticultural Science 72:503-517.

Pereira LS, et al (2015) Crop Evapotranspiration Estimation with Fao56: Past and Future. Agricultural Water Management 147:4-20.

Phyo AK, et al (2004) Storage Potential of Three Different Types of in-Shell Peanut Seeds under Ambient and Cold Room Conditions. National Science 38:21-30.

Pielke R, et al (2009) Climate Change: The Need to Consider Human Forcings Besides Greenhouse Gases. Earth and Space Science 90:413-414.

Ravishankara AR, et al (2009) Nitrous Oxide (N2o): The Dominant Ozone-Depleting Substance Emitted in the 21st Century. Science 326:123-125.

Raymundo R, et al (2018) Climate Change Impact on Global Potato Production. European Journal of Agronomy 100:87-98.

Rubenstein ES (2016) Immigration Drives U.S. Population Growth. in Negative Population Growth I (ed.).

Rupp DE, et al (2016) Seasonal Spatial Patterns of Projected Anthropogenic Warming in Complex Terrain: A Modeling Study of the Western Us. Climate Dynamics 48:2191-2213.

Saidur R, et al (2002) Role of Ambient Temperature, Door Opening, Thermostat Setting Position and Their Combined Effect on Refrigerator-Freezer Energy Consumption. Energy Conversion and Management 46:845-854.

Satterthwaite FE (1946) An Approximate Distribution of Estimates of Variance Components. Biometrics Bulletin 2:110-114.

Scherr SJ, et al (2012) From Climate-Smart Agriculture to Climate-Smart Landscapes. Agriculture & Food Security 1:12.

Scott D, et al (2008) Climate Change Vulnerability of the Us Northeast Winter Recreation–Tourism Sector. Mitigation and Adaptation Strategies for Global Change 13:577-596.

Shabbbar A, Bonsal B (2003) An Assessment of Changes in Winter Cold and Warm Spells over Canada. Natural Hazards 29:173-188.

Simon-Elorz K, Inchusta PS (1999) Information Technology for Inter-Organisational Systems: Some Evidence with Case Studies. International Journal of Information Management:75-86.

Singh N, et al (2016) Impact of Climate Change on Apple Production in India: A Review. Current World Environment 11:251-259.

Singh PK, et al (2017) Impact of Projected Climate Change on Rice (Oryza Sativa L.) Yield Using Ceres-Rice Model in Different Agrocliatic Zones of India. Current Science 112:108-115.

Soliman T, et al (2012) Quantitative Economic Impact Assessment of an Invasive Plant Disease under Uncertainty – a Case Study for Potato Spindle Tuber Viroid (Pstvd) Invasion into the European Union. Crop Protection 40:28-35.

Solomon S, et al (2010) Contributions of Stratospheric Water Vapor to Decadal Changes in the Rate of Global Warming. Science 324:1219-1223.

Spiegel DS, et al (2010) Generalized Milankovitch Cycles and Long-Term Climatic Habitability. The Astrophysical Journal 721:1308-1318.

Sue C, et al (2014) Staple Food Crops of the World. January 15 2020 https://www.nationalgeographic.org/maps/wbt-staple-food-crops-world/.

Sydeman WJ, et al (2014) Climate Change and Wind Intensificaiton in Coastal Upwelling Ecosystems. Science 345:77-80.

Tebaldi C, Knutti R (2007) The Use of the Multi-Model Ensemble in Probabilistic Climate Projections. Philosophical Transcations of the Royal Society A: Mathematical, Physical and Engineering Sciences 365:2053-2075.

U.N. (2015) U.N. Climate Change Conference Paris 2015. https://www.un.org/sustainabledevelopment/cop21/#FAQs.

UC (2019) Uc Cooperative Extension - Kern County. March 09 2019 http://cekern.ucanr.edu/.

UGA (2019) Food Preservation. April 20 2019 https://extension.uga.edu/topic-areas/food-health/food-preservation.html.

Usall J, et al (2015) Alternative Technologies to Control Postharvest Diseases of Stone Fruits. Stewart Postharvest Review 11:1-6.

USDA (1994) Ecoregions of the United States. https://www.fs.fed.us/rm/ecoregions/products/map-ecoregions-united-states/.

USDA (2016) The Commercial Storage of Fruits, Vegetables, and Florist and Nursery Stocks. in Gross KC, Wang CY, Saltveit M (eds.). Agricultural Research Service, Washington, D.C.

USDA (2018) Statistics by State. https://www.nass.usda.gov/Statistics_by_State/index.php.

USDA (2019) 2019 Census of Agriculture. in Agriculture USDo (ed.).

USGCRP (2014) Climate Change Impacts in the United States: The Third National Climate Assessment. U.S. Government Printing Office, U.S. Global Change Research Program.

USGS (2019) Watershed Map of North America. https://www.usgs.gov/media/images/watershed-map-north-america.

van Vuuren DP, et al (2011) The Representative Concentration Pathways: An Overview. Climatic Change 109:5-31.

Wang X, et al (2017) Postharvest Quality Monitoring and Variance Analysis of Peach and Nectarine Cold Chain with Multi-Sensors Technology. Applied Sciences 7.

Watson JA, et al (2016) Postharvest Storage, Packaging and Handling of Specialty Crops: A Guide for Florida Small Farm Producers. in Sciences H (ed.). University of Florida.

Weatherly JW, Rosenbaum MA (2017) Future Projections of Heat and Fire-Risk Indices for the Contiguous United States. Journal of Applied Meteorology and Climatology 56:863-876.

Winkler JA (2016) Embracing Complexity and Uncertainty. Annals of the American Association of Geographers 106:1418-1433.

Winkler JA, et al (2018) Potential Impacts of Climate Change on Storage Conditions for Commercial Agriculture: An Example for Potato Production in Michigan. Climatic Change 151:275-287.

Wolfe DW, et al (2007) Projected Change in Climate Thresholds in the Northeastern U.S.: Implications for Crops, Pests, Livestock, and Farmers. Mitigation and Adaptation Strategies for Global Change 13:555-575.

Wu J, et al (2014) Estimated Emissions of Chlorofluorocarbons, Hydrochlorofluorocarbons, and Hydrofluorocarbons Based on an Interspecies Correlation Method in the Pearl River Delta Region, China. Sci Total Environ 470-471:829-834.

Xiao Y (1999) Modelling Temperature-Dependency in Biology by Generalizing Temperature Coefficient Q10. Ecological Modelling 127:283-289.

Zhong W, Haigh J (2016) The Greenhouse Effect and Carbon Dioxide. Weather 64:100-1005.