



Impact of climate change on storage conditions for major agricultural commodities across the contiguous United States

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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project significant increases in SDD accumulation and decreases in winter subperiod length when compared with the historical reference period (1979–2005). Between years 2020 and 2080, Northwest and Northeast regions' apples will be impacted most by SDD accumulation with yearly increases between 261 and 1004 SDDs. Between years 2020 and 2080, Midwest regions' potatoes are projected to lose the most days of winter (24–39 days), and Southeast regions' peanuts will experience the greatest decrease in winter length (17–23%). 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 heterogeneous climate conditions at national scale, providing useful information for long-term agricultural storage planning.

Keywords Climate change · Postharvest crop storage · Storage degree days · Agricultural commodities · Contiguous United States

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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) suggest 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 (Fig. 1). Karl and Koss (1984) identified climate regions by taking the areal-weighted average of recorded temperature and precipitation distributions between years 1895 and 1983 for each state. Contiguous states with similar patterns and weightings were then grouped together to

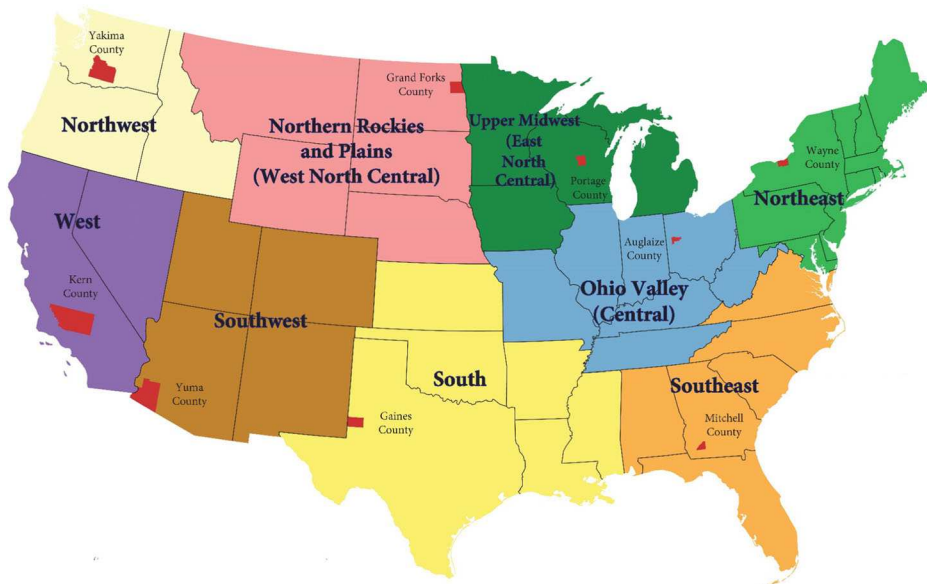


Fig. 1 Nine climate regions in the CONUS. We identified county regions (red-colored) of highest production for the highest grossing crop requiring cold storage. This map is adapted from Karl and Koss (1984)

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 and 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 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 and Supplemental Material Table S1) 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 ($T_{\max}$) and minimum temperature ($T_{\min}$) for years 1979–2005 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). The 26-year time slice (1979–2005) 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 ~4 km 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).

Table 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 A summary of crop identification, storage facility location, city coordinates, typical planting and harvesting dates, crop storage dates, and base temperature for crop storage

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/ <i>Runner</i>	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/ <i>Runner</i>	Golden Peanut Com- pany	Gaines County, Seminol- e, 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

2.3 Future climate projections

The 20 statistically downscaled Coupled Model Intercomparison Project Phase 5 (CMIP5) GCMs $T_{\max}$ and $T_{\min}$ daily projections from years 2020–2080 were derived from the MACAv2 database (Abatzoglou and Brown 2012), at <http://www.climatologylab.org/maca.html>. Historical baseline and projected temperature data from MACAv2 downscaled GCMs were extracted at the location of the representative storage facility for each region, as identified in Table 2. The horizontal resolution for MACAv2 downscaled GCMs was generated at ~4 km or 1/24th degree and over the CONUS. The 20 downscaled GCMs ensembles (Table 3) included historical baseline, 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 ~650 ppm; for RCP8.5, CO₂ concentrations rise until the end of the twenty-first century and peak at ~1370 ppm (Moss et al. 2010).

Future climate projections were divided into 3 time slices for analysis: early-century (2020–2040), mid-century (2040–2060), and late-century (2060–2080). Historical baseline simulations from each GCM were extracted for 1979–2005. The delta change factor method was utilized to produce projected daily temperature for each location (Anandhi et al. 2011; Winkler et al. 2018). The delta factor for each location was calculated as the difference of the monthly average of $T_{\max}$ and $T_{\min}$ from each future time slice and each RCP scenario with the historical baseline. The monthly delta factor was then added to the daily observed gridMET historical $T_{\max}$ and $T_{\min}$ from 1979 to 2005 for each location. Accordingly, there was a total of 240 monthly delta values (12 months × 20 GCMs) calculated for each location, time slice, and

Table 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	UK	Met Office Hadley Center
11	HadGEM2-CC	UK	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

RCP. The monthly delta factors were then added to daily gridMET data to produce future daily $T_{\max}$ and $T_{\min}$ projections for each location, time slice, GCM, and RCP.

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:

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

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 (1979–2005) 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 a continuous period with relatively cool temperature (i.e., little accumulation in SDDs) compared with the other periods. It is considered 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 (1979–2005) 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 1979–2005 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 with 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 was 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 (Fig. 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 ($p < 0.01$) increase by the early-, mid-, and late-century time slice in mean

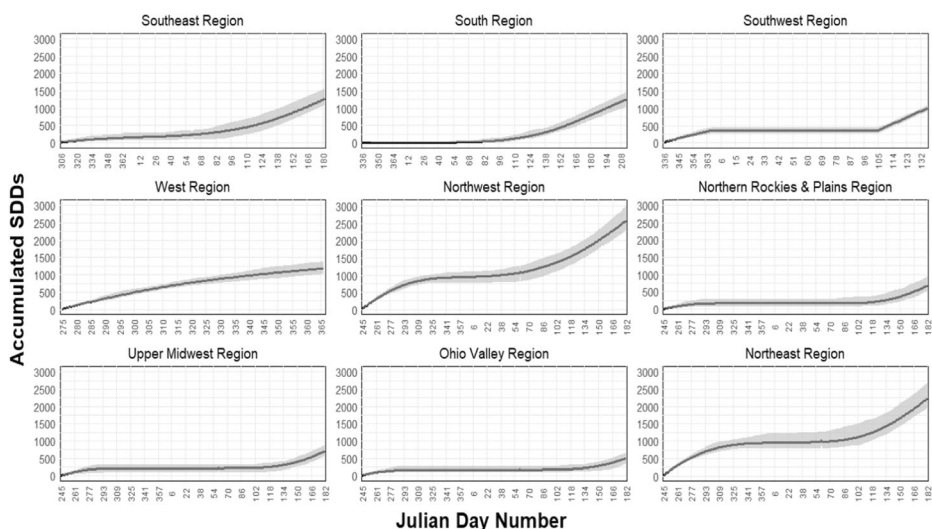


Fig. 2 Maximum, minimum, and mean daily accumulation of storage degree days (SDDs) during the storage season of each region for 1979–2005 (historical reference period). The first Julian day for each region represents the typical first day of storage for that particular crop. The daily SDDs were smoothed using a 7-day moving average to minimize day-to-day fluctuations

SDD accumulation and SDD percentage change when compared with their historical reference period.

For RCP4.5, mean SDD accumulation during the early-century ranges from a minimum increase of 57.8 SDDs in the Southwest region (lettuce) to a maximum increase of 341.1 SDDs in the Northwest region (apples) (Fig. 3a, b, c), indicating higher storage costs. Mid-century changes range from a minimum increase of 106.7 SDDs in the Southwest region (lettuce) to a maximum increase of 505.7 SDDs in the Northwest region (apples). Late-century changes range from a minimum increase of 127.8 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 97.5 SDDs and Northwest region (apples) will be most impacted with an average yearly increase of 504.3 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 in the Northwest region (apples), Fig. 4 displays the maximum and minimum range for all GCMs for each RCP and time slice. All other regional SDD uncertainty ranges are provided in the Supplemental Material Fig. S1 to S8.

When looking at the percentage change in SDD accumulation for future time slices under RCP4.5 (Fig. 5a, b, c), some regions appear to be impacted more despite having lower absolute rates of SDD accumulation (Fig. 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 5.3% in the Southwest region (lettuce) to a maximum increase of 28.5% in the Upper Midwest region (potatoes). Mid-century changes range from a minimum increase of 9.6% in the Southwest

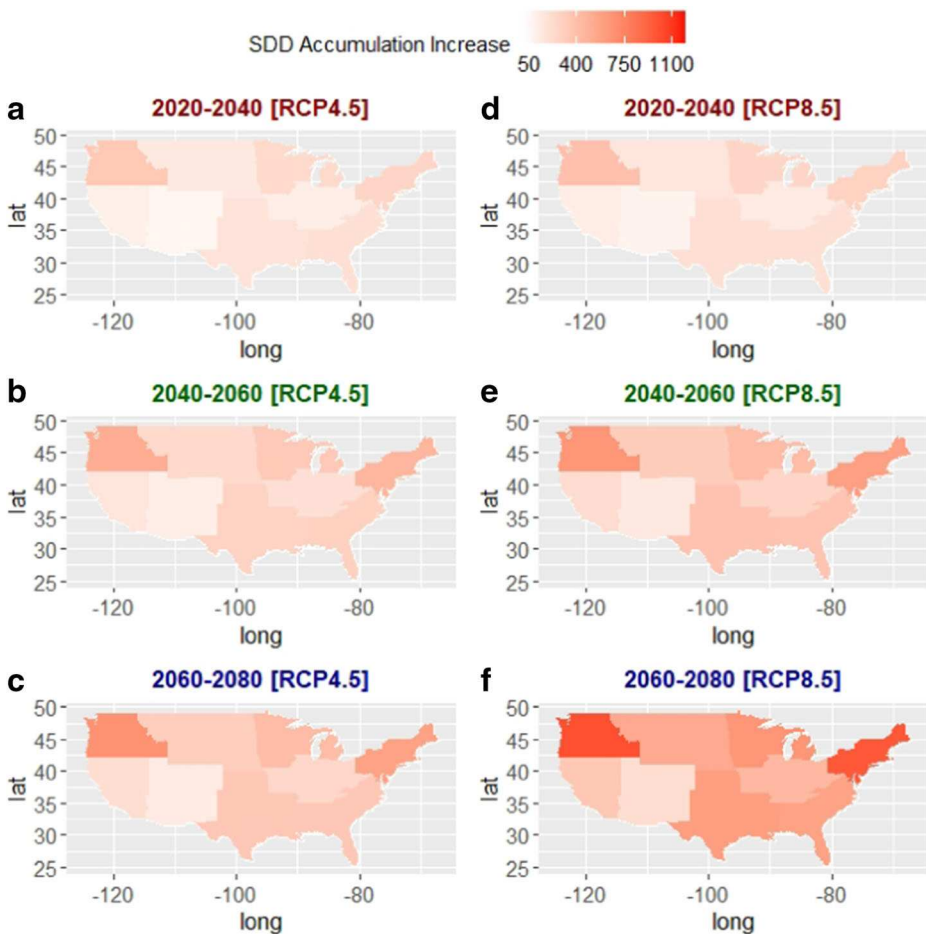


Fig. 3 Projected SDD accumulation by region in the early, mid-, and late-century time slice for RCP4.5 (a, b, c) and RCP8.5 (d, e, f). Final projected value(s) for SDD accumulation were averaged over the 20 GCMs on the final day of storage for each specific region. Highest increases in SDD accumulation are displayed in dark red

region (lettuce) to a maximum increase of 38.7% in the Upper Midwest region (potatoes). Late-century changes range from a minimum increase of 11.5% in the Southwest region (lettuce) to a maximum increase of 45.5% in the Upper Midwest region (potatoes). When examining the yearly mean of all three future time slices, the Southwest region (lettuce) will be least impacted with an average yearly SDD increase of 8.8% while the Upper Midwest region (potatoes) will be most impacted with an average yearly SDD increase of 37.6%.

All regions in RCP8.5 scenarios project significant ($p < 0.01$) increases in mean SDD accumulation by the early-, mid-, and late-century time slice when compared with their historical reference period (Fig. 3d, e, f). Due to higher CO_2 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 72.6 SDDs in the Southwest region (lettuce) to a maximum increase of 386.7 SDDs in the Northwest region (apples). Mid-century changes range from a minimum increase

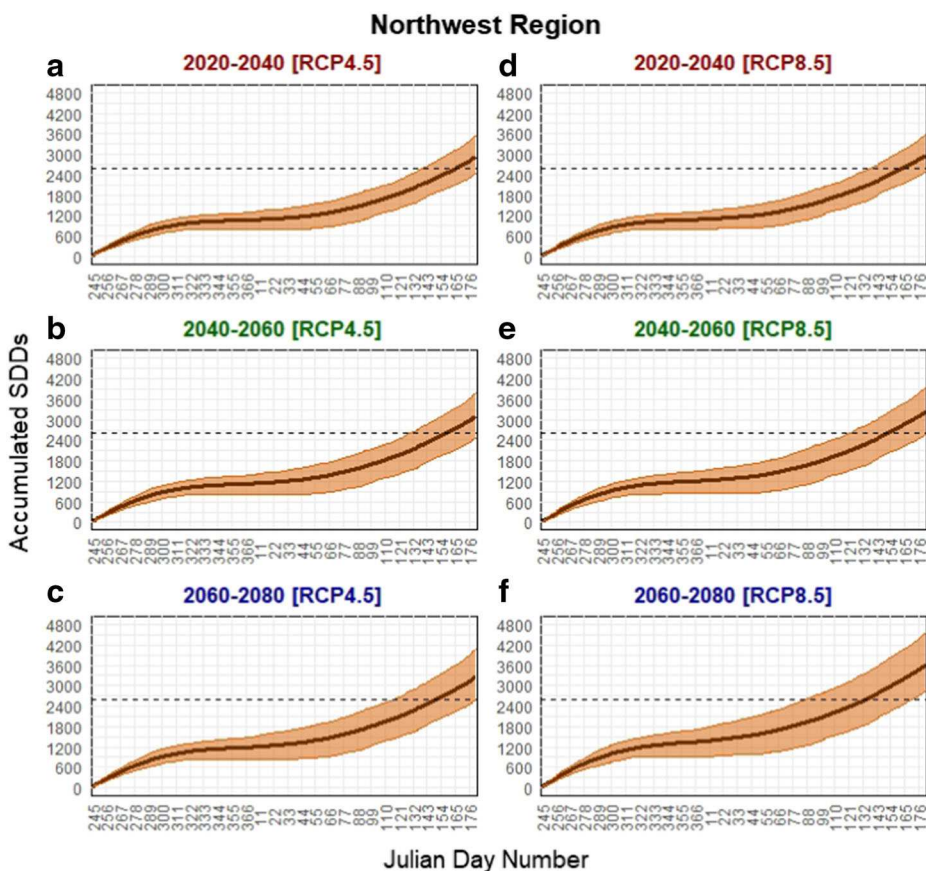


Fig. 4 Projected SDD accumulation during the storage period (Sept. 1–Jun. 30) for Northeast region (apples) for RCP4.5 (a, b, c) and RCP8.5 (d, e, f). Projected SDD accumulation for maximum and minimum GCM values are displayed in the red ribbon, and the mean of all GCMs is represented by the dark red line. Historical mean SDD accumulation on final day of storage (Jun. 30) is represented by the horizontal dashed line

of 140.0 SDDs in the Southwest region (lettuce) to a maximum increase of 649.3 SDDs in the Northwest 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 140.9 SDDs and the Northwest region (apples) will be most impacted with an average yearly increase of 679.8 SDDs.

RCP8.5 early-century changes in percentage difference in SDD accumulation range from a minimum increase of 6.7% in the Southwest region (lettuce) to a maximum increase of 31.1% in the Upper Midwest region (potatoes) (Fig. 5d, e, f). Mid-century changes range from a minimum increase of 12.4% in the Southwest region (lettuce) to a maximum increase of 46.2% in the Upper Midwest region (potatoes). Late-century changes range from a minimum increase of 18.1% in the Southwest region (lettuce) to a maximum increase of 63.2% in the Upper Midwest region (potatoes). When examining the mean of all three future time slices, the Southwest region (lettuce) will be least impacted with an average SDD increase of 12.4% and

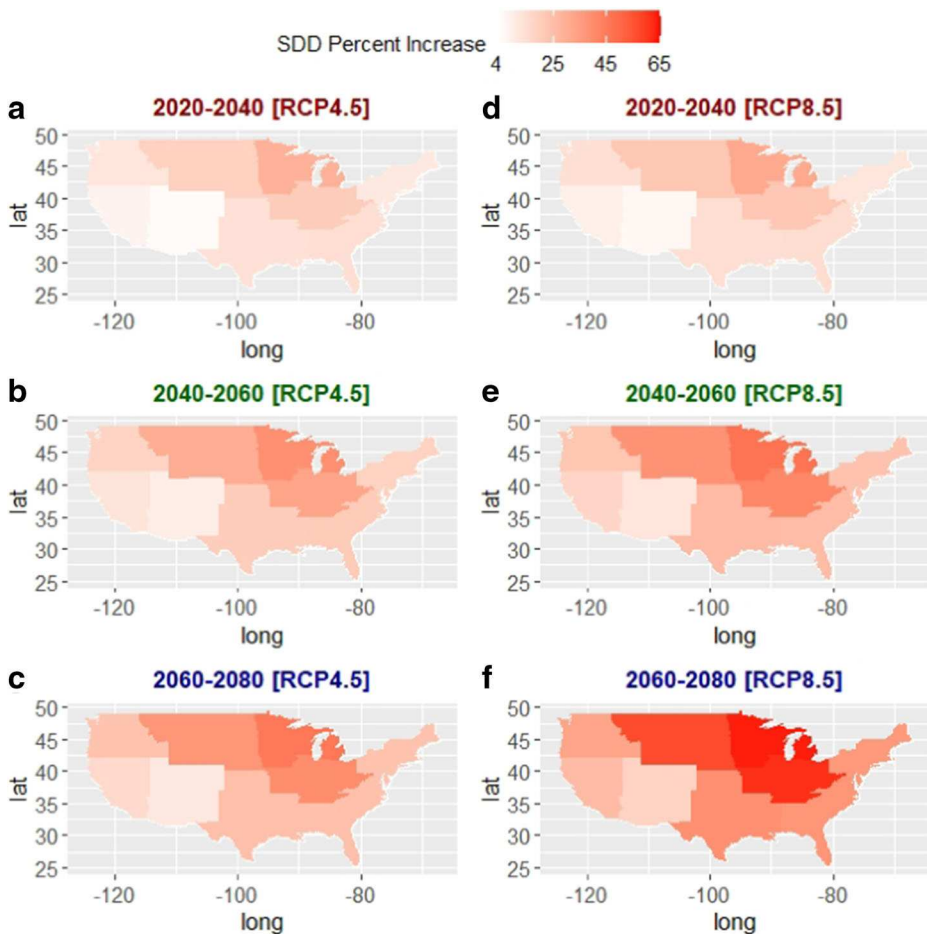


Fig. 5 Projected SDD accumulation percentage increase by region in the early-, mid-, and late-century time slice for RCP4.5 (a, b, c) and RCP8.5 (d, e, f). Final projected value(s) for SDD percentage change were averaged over the 20 GCMs on the final day of storage for each specific region. Highest increases in SDD percentage are displayed in dark red

the Upper Midwest region (potatoes) will be most impacted with an average SDD increase of 46.8%.

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 Fig. 6. 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.

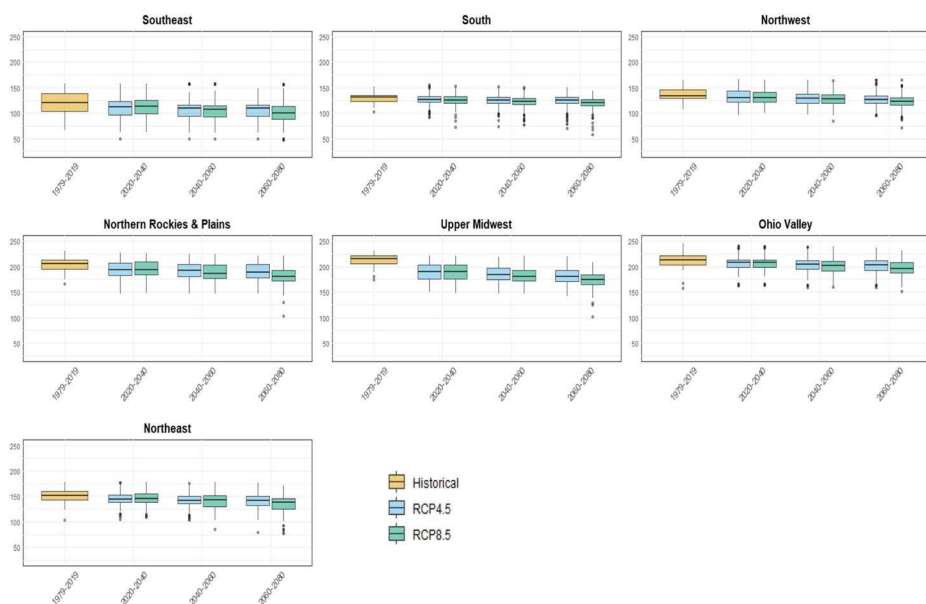


Fig. 6 Length of winter subperiod by region in the early-, mid-, and late-century time slice for historical, RCP4.5, and RCP8.5. Southwest and West region(s) did not have a winter subperiod for historical or projected time slices

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 ($p < 0.05$) decrease by the early-, mid-, and late-century time slice in mean length of winter subperiod and winter percentage change compared with their historical reference period. Early-century decreases in mean length of winter subperiod range from the smallest loss of 3.3 days in the South region (peanuts) to the largest loss of 23.7 days in the Upper Midwest region (potatoes) (Fig. 7a, b, c), indicating less cost-effective storage days. Mid-century decreases range from the smallest loss of 4.2 days in the South region (peanuts) to the largest loss of 27.5 days in the Upper Midwest region (potatoes). Late-century decreases range from the smallest loss of 5.3 days in the South region (peanuts) to the largest loss of 30.9 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 4.3 winter days and the Upper Midwest region (potatoes) will be most impacted with a yearly loss of 27.4 winter days.

RCP4.5 early-century differences in percentage decrease in length of winter subperiod range from a minimum loss in winter days of 5.8% in the South region (peanuts) to a maximum loss of 16.9% in the Southeast region (peanuts) (Fig. 8a, b, c). Mid-century differences range from a minimum loss of 6.3% in the South region (peanuts) to a maximum loss of 17.8% in the Southeast region (peanuts). Late-century differences range from a minimum loss of 6.7% in the South region (peanuts) to a maximum loss of 17.9% 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

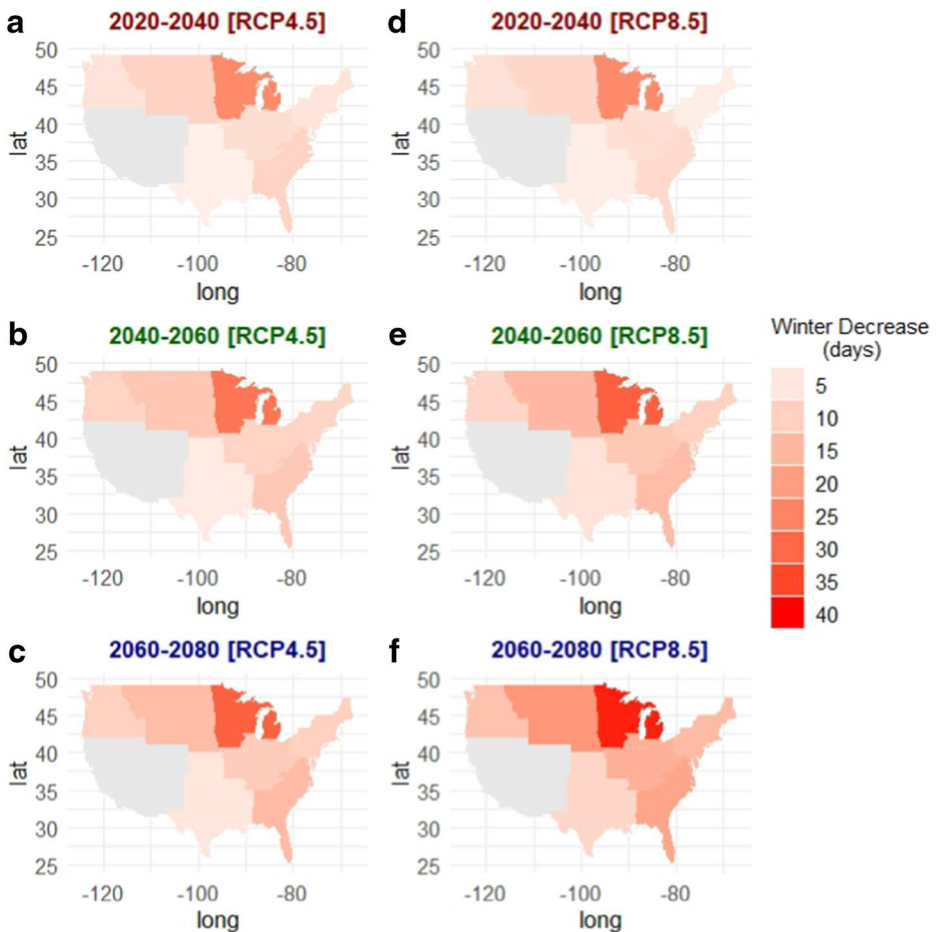


Fig. 7 Projected decrease in length of winter subperiod by region in the early-, mid-, and late-century time slice for RCP4.5 (a, b, c) and RCP8.5 (d, e, f). Highest decreases in winter length are displayed in dark red. Southwest and West regions did not have a winter period and are displayed in gray

of 6.3% and the Southeast region (peanuts) will be most impacted with an average yearly decrease in winter length of 17.5%.

All regions in RCP8.5 project a significant ($p < 0.05$) decrease by the early-, mid-, and late-century time slice in mean length of winter subperiod and winter length percentage change compared with the historical reference period. Due to higher CO_2 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 3.6 days in the South region (peanuts) to the largest loss of 23.6 days in the Upper Midwest region (potatoes) (Fig. 7d, e, f). Mid-century decreases range from the smallest loss of 6.0 days in the South region (peanuts) to the largest loss of 31.1 days in the Upper Midwest region (potatoes). Late-century decreases range from the smallest loss of 8.4 days in the South region (peanuts) to the largest loss of 38.7 days in the Upper Midwest region (potatoes). When examining the yearly mean of all

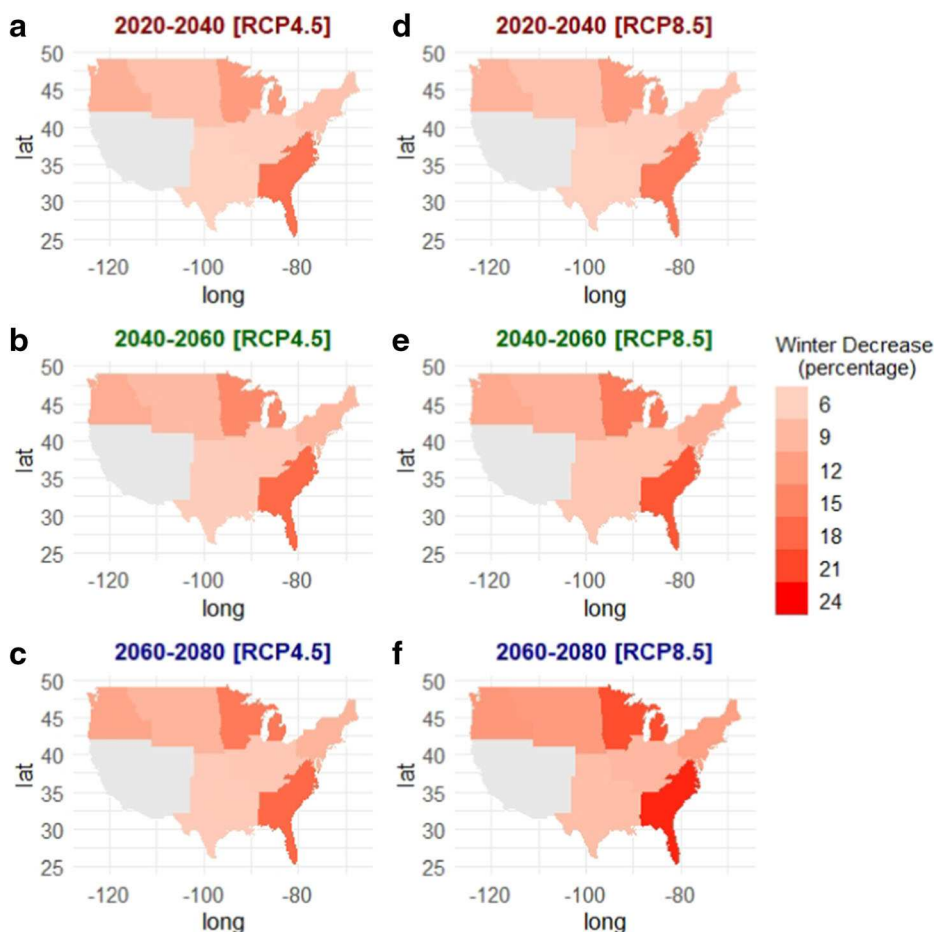


Fig. 8 Projected percentage decrease in length of winter by region in the early-, mid-, and late-century time slice for RCP4.5 (a, b, c) and RCP8.5 (d, e, f). Highest decreases in winter percentage change are displayed in dark red. Southwest and West regions did not have a winter period and are displayed in gray.

three future time slices, the South region (peanuts) will be least impacted with an average yearly loss of 6.0 days and the Upper Midwest region (potatoes) will be most impacted with an average yearly loss of 31.1 days.

RCP 8.5 early-century differences in percentage decrease in length of winter subperiod range from a minimum loss in winter days of .8% in the South region (peanuts) to a maximum loss of 16.3% in the Southeast region (peanuts) (Fig. 8d, e, f). Mid-century differences in winter length range from a minimum loss of 7.0% in the South region (peanuts) to a maximum loss of 19.6% in the Southeast region (peanuts). Late-century decreases in winter length range from a minimum loss of 8.2% in the South region (peanuts) to a maximum loss of 23.0% 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 7.0% and the Southeast region (peanuts) will be most impacted with an average yearly decrease in winter length of 19.6%.

4 Discussion

4.1 Most impacted crops and regions in CONUS

All regions are anticipated to have yearly increases between 58 and 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 261 and 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 twenty-first 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 5 and 63%. 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 (≈ 27.3 days and ≈ 31.1 days each year for RCP4.5 and RCP8.5, respectively). This implies that storage costs are expected to be much higher in this region under future scenarios since there are ~ 27 and ~ 31 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 ($\sim 17.5\%$ decrease and $\sim 19.6\%$ each year for RCP4.5 and RCP8.5, respectively). 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 (Figs. 3 and 6, 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 US 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).

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). 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. The delta change factor method used in this study does allow for climate impact assessment based on historical daily climate measurements and GCMs historical simulations and future projections, but the delta method does not take into consideration changes in future climate variability, such as extreme warm or cold spells (Winkler et al. 2018). It is important to note that the magnitude of projected changes in SDD accumulation is larger for RCP8.5 than RCP4.5, further reflecting uncertainty. When utilized correctly, GCM 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 US 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 with 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.

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