

Article

Severe Convective Weather in the Central and Eastern United States: Present and Future

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Abstract: The continental United States is a global hotspot of severe thunderstorms and therefore is particularly vulnerable to social and economic damages from high-impact severe convective weather (SCW), such as tornadoes, thunderstorm winds, and large hail. However, our knowledge of the spatiotemporal climatology and variability of SCW occurrence is still lacking, and the potential change in SCW frequency and intensity in response to anthropogenic climate warming is highly uncertain due to deficient and sparse historical records and the global and regional climate model's inability to resolve thunderstorms. This study investigates SCW in the Central and Eastern United States in spring and early summer for the current and future warmed climate using two multi-year continental-scale convection-permitting Weather Research and Forecasting (WRF) model simulations. The pair of simulations consist of a retrospective simulation, which downscales the ERA-Interim reanalysis during October 2000–September 2013, and a future climate sensitivity simulation based on the perturbed reanalysis-derived boundary conditions with the CMIP5 ensemble-mean high-end emission scenario climate change. A proxy based on composite reflectivity and updraft helicity threshold is applied to infer the simulated SCW occurrence. Results indicate that the retrospective simulation captures reasonably well the spatial distributions and seasonal variations of the observed SCW events, with an exception of an overestimate along the Atlantic and Gulf coast. In a warmer-moister future, most regions experience intensified SCW activity, most notably in the early-middle spring, with the largest percentage increase in the foothills and higher latitudes. In addition, a shift of simulated radar reflectivity toward higher values, in association with the significant thermodynamic environmental response to climatic warming, potentially increases the SCW severity and resultant damage.

Keywords: severe convective weather; thunderstorm; convection-permitting; regional climate simulation; pseudo global warming



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1. Introduction

Severe thunderstorms are ubiquitous in the Central and Eastern United States during the spring and summer seasons, and the associated occurrence of large hail, thunderstorm winds, and tornadoes, which herein are collectively referred to as severe convective weather (SCW), incurs a large amount of economic and societal losses. According to the statistics by NOAA's National Centers for Environmental Information, for example, SCW accounted for 41.6% of the U.S. billion-dollar disaster events from 1980 to 2017 and caused a total damage of USD 206.1 billion and was responsible for 1578 fatalities [NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2018; <https://www.ncdc.noaa.gov/billions/>) (accessed on 15 June 2018)]. Despite the significant importance to the national economy and livelihood, considerable uncertainties exist in SCW occurrence, especially its regional climatology, temporal variability, long-term trend, and potential response to anthropogenic global warming.

One barrier to the SCW research is the absence of a reliable, long historical observation record because of the often-subjective observation nature of the record and the inconsistent practices for data collection between different regions and countries and between different time periods. In the U.S., the primary source of the publicly available SCW information is the storm events database compiled by the NOAA Storm Prediction Center [1]. This database has been widely used for climatological studies of severe thunderstorms (e.g., [2–8]). As indicated in previous studies, however, this storm report dataset suffers from some problems. For example, the SCW record is mainly based on eyewitness reports and damage assessment and therefore is highly dependent on observer availability. As a result, observed SCW activities and trends could skew heavily toward densely populated areas. Other influential non-meteorological factors include the non-uniform standards and changing procedures for estimating intensity and damages, all giving rise to artificial variability trends that are hard to characterize, as indicated in a critical review by [9].

Given the fact that the existing SCW observation records are too problematic to be used for the direct analysis of temporal and spatial variability, an effort has been made to use meteorological covariates to estimate the severe thunderstorm occurrence. [The more recent record is comparatively more reliable]. As pioneered by [4], this alternative approach involves the identification of SCW favorable large-scale environments based on reanalysis-derived proximity soundings and the development of connections between sounding-derived environmental variables and severe weather events. One commonly-used SCW discriminator is a combination of convective available potential energy (CAPE) and shear in a deep tropospheric layer, namely a weighted product of the two values exceeding an imposed threshold magnitude (e.g., [4,10–12]). Such severe thunderstorm environments discriminators have been applied to global climate models (GCMs) to evaluate the model's capability to represent convective environments in the current climate and assess the influence of climate warming on convective environments (e.g., [13–17]). An attractive feature of this approach is that it enables an exploration of the past trend using the long-term historical reanalysis product and the potential changes in the future using GCM projections for various climate warming scenarios. An apparent weakness is that this approach bypasses the storm initiation issue as pointed out in [9,18]; a favorable environment (i.e., high CAPE and shear) cannot guarantee the actual occurrence of a severe storm without an adequate triggering mechanism. Another problem is the climate model's fidelity in realistically producing the storm environments.

High-resolution regional climate models at convection-permitting grid spacing (typically ≤ 4 km) provide a promising solution to these limitations associated with the favorable environments approach and their utilization as SCW historical climatology, and such models have been used to explore climate change impact on SCW over the continental U.S. ([18–22]). This approach determines SCW from simulated reflectivity and updraft helicity or upward vertical velocity, demonstrating an impressive potential in capturing many observed climatological features. There are several advantages over the GCM environmental parameter-based method. First, convection-permitting models explicitly resolve convective storms, therefore avoiding the uncertainty about whether, where, and when storms form in coarse-resolution climate models under a favorable environment. Second, severe weather events are highly localized, and their genesis is commonly associated with some mesoscale processes, such as mesoscale terrain forcing, gust fronts, and dry lines, all of which are missing in climate models but can be properly depicted in convection-permitting models. Additionally, the exclusion of error-prone cumulus parameterizations improves the model's ability to represent propagating convection that is initiated on the high terrain of the Rocky Mountains in the afternoon-evening hours and then travels eastward during the night through the Great Plains, leading to frequent occurrence of hazardous weather in the central U.S. ([23–26]). Other benefits from the use of convection-permitting resolution include the explicit depiction of various convective morphologies with each being conducive to specific hazardous weather and the improved representation of diurnal convection (e.g., [27–30]), with the latter being relevant to the replication of observed diurnal SCW behavior.

This study examines the SCW occurrence in the Central and Eastern U.S. in spring and early-summer using a pair of multi-year continental-scale convection-permitting simulations reported in [31]. The major objectives are (1) to evaluate the performance of a convection-permitting model to capture the spatiotemporal patterns of SCW events, (2) to assess SCW changes in frequency, seasonality, and intensity in a warmer climate, and (3) to investigate the controlling environmental variables. Section 2 describes the severe thunderstorm report database, simulations, and methodology. Results of current and future climate simulations are presented in Section 3, along with the observed climatology. A summary and conclusions are provided in Section 4.

2. Numerical Simulations, Data and Method

2.1. Numerical Simulations

Two sets of Weather Research and Forecasting (WRF) model simulations from [31] are used in this study to examine U.S. severe convective weather in current and future warmer climates. As described in [31], the computational domain encompassed much of North America, including the contiguous U.S. (CONUS), Northern Mexico, and Southern Canada at a 4 km horizontal grid spacing. The employed subgrid parameterizations are Thompson-Eidhammer microphysics [32], Yonsei University (YSU) planetary boundary layer [33], Rapid Radiative Transfer Model (RRTMG; [34]), and Noah-MP land-surface model [35]. Significant improvements were made to the land surface model and lake water temperature treatment to improve model performance. In addition, spectral nudging was applied to large scales (i.e., ~2000 km and above) in horizontal wind, geopotential, and temperature above the planetary boundary layer. For detailed model configuration, the reader is referred to [31].

The current climate simulation spanned a 13-year period from October 2000 to September 2013, with the initial and boundary conditions being specified from the 6-hourly ERA-Interim reanalysis data [36]. An extensive evaluation of this retrospective simulation has been performed in previous studies, showing good agreement with observations for the spatial and temporal pattern of sub-seasonal and seasonal precipitation and temperature in most of CONUS [31], main characteristics of propagating mesoscale convective systems (MCSs) [37], diurnal precipitation cycle [38], and precipitation extremes ([39,40]). These results lend confidence in investigating the simulated severe convective weather.

The future climate simulation used by [31] to project the end-of-century climate changes under a business-as-usual emissions scenario follows the pseudo global warming (PGW) approach, which was pioneered by [41] and used widely in climate change studies using dynamical downscaling (e.g., [42–45]). This future simulation covered the same 13-year period as the current climate simulation, but with the reanalysis-generated initial and boundary conditions being perturbed according to two CMIP5 multi-model ensemble mean climates:

$$\text{WRF}_{\text{input}} = \text{ERA-Interim} + \Delta\text{CMIP5}_{\text{RCP8.5}} \quad (1)$$

$$\Delta\text{CMIP5}_{\text{RCP8.5}} = \text{CMIP5}_{2071-2100} - \text{CMIP5}_{1976-2005} \quad (2)$$

where $\Delta\text{CMIP5}_{\text{RCP8.5}}$ is the 19 CMIP5 model ensemble-mean change signal under the RCP8.5 emission scenario between a 30-year historical period (1976–2005) and the end-of-century 30-year period (2071–2100). The perturbed physical fields are geopotential, horizontal wind, temperature, specific humidity, sea surface temperature, soil temperature, and sea ice. More information on the design of these simulations can be found in [31].

Unlike the traditional dynamical downscaling, where coarse resolution GCMs provide initial and boundary conditions for high resolution regional climate models over a region of interest, the PGW approach takes the initial and boundary conditions as a superimposition of 6-hourly reanalysis data and the GCM projected monthly climate change signals. It is therefore anticipated that the lateral boundary forcing in the PGW simulation would have mean climatological conditions similar to the GCM projected future state, but the daily weather perturbations are comparable to those observed in the present time. This unique

feature enables us to investigate the impact of global warming by a direct comparison between a present year and the corresponding PGW year in the context of interannual variations. As noted in [31], the imposed climate perturbation (i.e., $\Delta\text{CMIP5}_{\text{RCP8.5}}$) features a robust signature of warming and moisture enhancement but rather weak circulation changes, suggestive of the predominant impact of thermodynamic changes over dynamic changes. As such, the PGW technique approximately preserves the occurrence of synoptic-scale weather systems in the current climate while allowing for their changes and the development of smaller scale processes in response to the climatic warming.

2.2. Observational Data

The observational SCW data were obtained from the NOAA National Climatic Data Center (NCDC) publication Storm Data compiled by the Storm Prediction Center (SPC). The data currently contains information on severe thunderstorms (e.g., location, event type, intensity) from 1950 through 2017 (<https://www.ncdc.noaa.gov/stormevents/>) (accessed on 15 June 2018). Events classified as tornado, hail, and thunderstorm wind were used in this study. Thunderstorm wind is defined as convective weather-induced damaging wind, which is different from the event type of high wind, which is non-convective damaging wind. As indicated above, the storm observations are mostly from eyewitness reports and post damage assessments. As such, they are affected by non-meteorological factors and are particularly problematic in trend analysis. Notwithstanding, this is the most comprehensive SCW source available for climatological research and model validation in the U.S.

2.3. Methodology

Although the simulations capably resolve convective storms, such as MCSs, as demonstrated in [37], the 4 km spatial resolution is still insufficient to directly resolve all of the interested SCW phenomena, such as tornadoes. Therefore, a SCW model proxy was sought to estimate SCW occurrence in our simulations. As in a few previous studies ([18–20,22]), our SCW proxy builds upon the hourly simulated composite radar reflectivity (Z) and 3-hourly updraft helicity (UH) over the 2–5 km layer above the ground [46] and requires the co-occurrence of these values at the same grid point exceeding a specified threshold.

$$Z \geq 55 \text{ dBZ}; \text{UH} \geq 60 \text{ m s}^{-1} \quad (3)$$

These Z-UH thresholds are selected by trial and error on the basis of a quantitative comparison with the aforementioned NCDC storm reports, and they are somewhat larger than optimal values utilized in some previous studies. For example, [18,19] adopted the 50–40 Z/UH and 40–60 Z/UH combination, respectively, for best agreement between modeled and observed SCW occurrences. The SCW detection with this Z-UH based proxy is generally more sensitive to the choice of Z threshold than the UH threshold. Lower values as used in previous studies led to an overestimation of SCW events in our tests. A preliminary analysis showed that our retrospective simulation realistically reproduced the observed composite radar reflectivity spectra from the Next Generation Weather Radar (NEXRAD) level II data, except for an excess in low reflectivity ranges (<10 dBZ) (Jason Flemke, personal communication).

The model proxy is applied to the hourly Z and 3-hourly UH data at each grid point. Where and when the Z-UH threshold pair are simultaneously met, a SCW event is assigned to the corresponding grid point and time. Subsequently, the 3-hourly SCW is summed at each grid point to determine daily SCW results. For comparison, each observed event is assigned to the closest model grid point and summed each day for the gridded daily reports. The daily data in both the model and observations are then regridded to a common $40 \times 40 \text{ km}^2$ grid. A similar coarsening was employed in preceding studies (e.g., [18,19]) to reduce the uncertainties in the observed timing and location. The present study focuses on the Central and Eastern U.S. (roughly east of the continental divide) during the months March–June. July–August was not examined in this study because the dry-warm model bias reported in [31] makes us less confident about the SCW analysis during this period.

3. Results

3.1. Observed SCW Climatology

We first examine the observed climatological features of severe thunderstorm activity during 2001–2013. Figure 1 shows the spatial distributions of each of the three categories and all categories of severe weather examined herein, corresponding to the accumulated March–June counts of SCW reports averaged over the 13 years. It is readily seen that SCW is ubiquitous, widely spread east of the Continental Divide with two broad regions of active occurrence (Figure 1a). The maximum reports are centered in the central Great Plains, mainly covering Oklahoma, Kansas, Northern Texas, Southern Nebraska, and the western flank of the Ozark Mountains. The secondary maximum is located east of the Mississippi River and south of the Ohio River, including east Kentucky and Tennessee, north Alabama and Georgia, most of South Carolina, and Western North Carolina and Virginia. There are many localized hotspots outside these two concentrated geneses, suggestive of a large spatial variability. The elongated high frequency across the lower Northeast and upper Southeast, as well as the narrow prolific genesis in east Tennessee, is indicative of the topographic impact of the Appalachian Mountains. It is interesting that SCW is relatively less common along the Mississippi and Ohio Rivers. As well as the Rocky Mountains, the Gulf coasts and the northernmost states are comparatively unfavorable for SCW occurrence during the spring and early summer. When stratified by the SCW types (Figure 1b–d), hail events are dominant, and tornado events are least, with damaging winds being in-between. The regional preference varies between the severe weather categories. For instance, hailstorms are more common in the central U.S. than in the east, accounting for the maximum SCW; in contrast, damaging wind events associated with convection are more frequently reported in the Eastern U.S., attributable to the secondary SCW maximum (Figure 1a). Tornado peaks are roughly collocated with the SCW maximum in the Central Plains. Lastly, it is worth mentioning that despite a moderate interannual variability, there is no discernible trend during the 2001–2013 period for all SCW events or each individual category of SCW event (not shown).

The monthly climatology in Figure 2 displays a steady increase as the season progresses from early spring to summer; the total reports in the domain increase by a factor of 4.3 between March–June. The spatial distribution also undergoes considerable transitions, showing an overall northward and westward expansion with season. In March, storm activity is largely confined to the south of $\sim 40^\circ$ N and east of $\sim 100^\circ$ W, extending to the Northern Ohio Valley and Southern Upper Midwest in April and spreading over most of the Northern Great Plains, Upper Midwest, and Northeast by May. In June, the storm occurrence spreads further over the Northern Rockies. Along with the areal expansion, the peak in SCW frequency shifts toward the Rocky Mountains and the Atlantic coast. The May–June monthly reports account for the primary seasonal maximum in the Central Plains (Figure 1a), while the June monthly reports alone are responsible for the secondary maximum near the Appalachian Mountains. Salient distinctions exist in both the frequency and spatial seasonality between severe weather types (not shown). For example, hail is most frequently reported in Kansas, Oklahoma, Northern Texas, and the western portion of the Ozark Mountains in March and April. As the season progresses, the primary peak area moves closer to the Rocky Mountains. In early summer (May–June), hail events also become more frequent to the east of the Appalachian Mountains as well as in northern states. Not surprisingly, the spatial distribution of tornado occurrence and its evolution with season is very similar to hail, except for the secondary area mentioned above. Thunderstorm wind observations are dominant in the Tennessee Valley west of the Appalachian Mountains in spring (March–April), and the area expands along the eastern side of the Appalachian Mountains and to the upper Midwest in early summer (May–June).

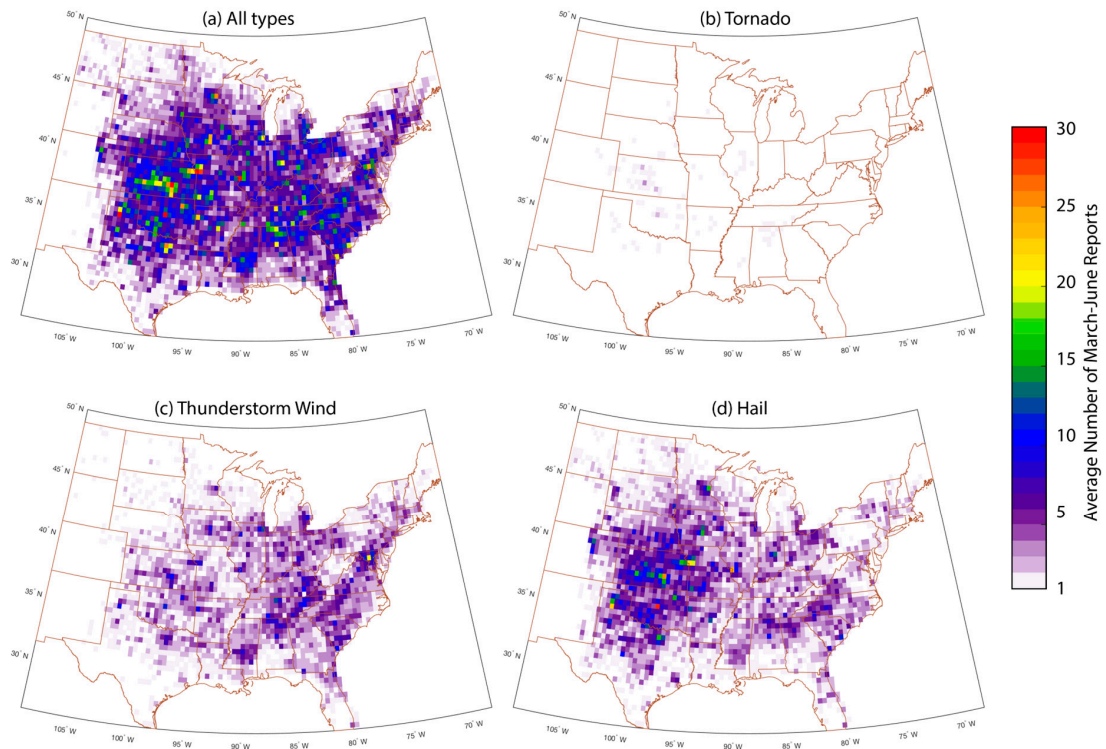


Figure 1. Thirteen-year average of March-June report counts (from 2001 to 2013) for (a) all SCW types, (b) Tornado, (c) thunderstorm winds, and (d) hail. These are observed SCW from NOAA National Climatic Data Center (NCDC) publication Storm Data compiled by the Storm Prediction Center (SPC).

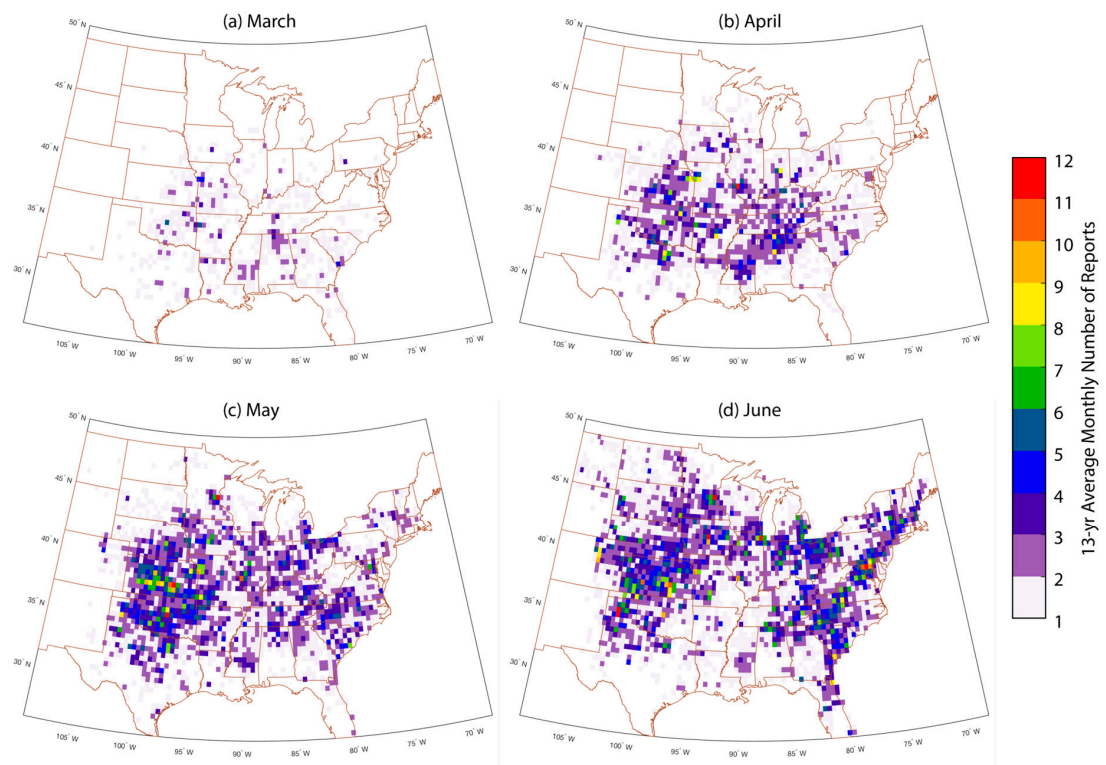


Figure 2. Thirteen-year average monthly number of reports of all SCW types for (a) March, (b) April, (c) May, and (d) June. These are observed SCW from NOAA National Climatic Data Center (NCDC) publication Storm Data compiled by the Storm Prediction Center (SPC).

Significant diurnal variations are present, with stronger signals in warmer months as demonstrated in Figure 3. Independent of the month, all SCW reports peak at 22 UTC (i.e., middle to late afternoon) and have a minimum between 8 and 15 UTC (i.e., late night to early morning). Similar diurnal behaviors are observed for individual weather types, especially for hail and damaging winds. Tornado reports exhibit a flat and slightly delayed maximum.

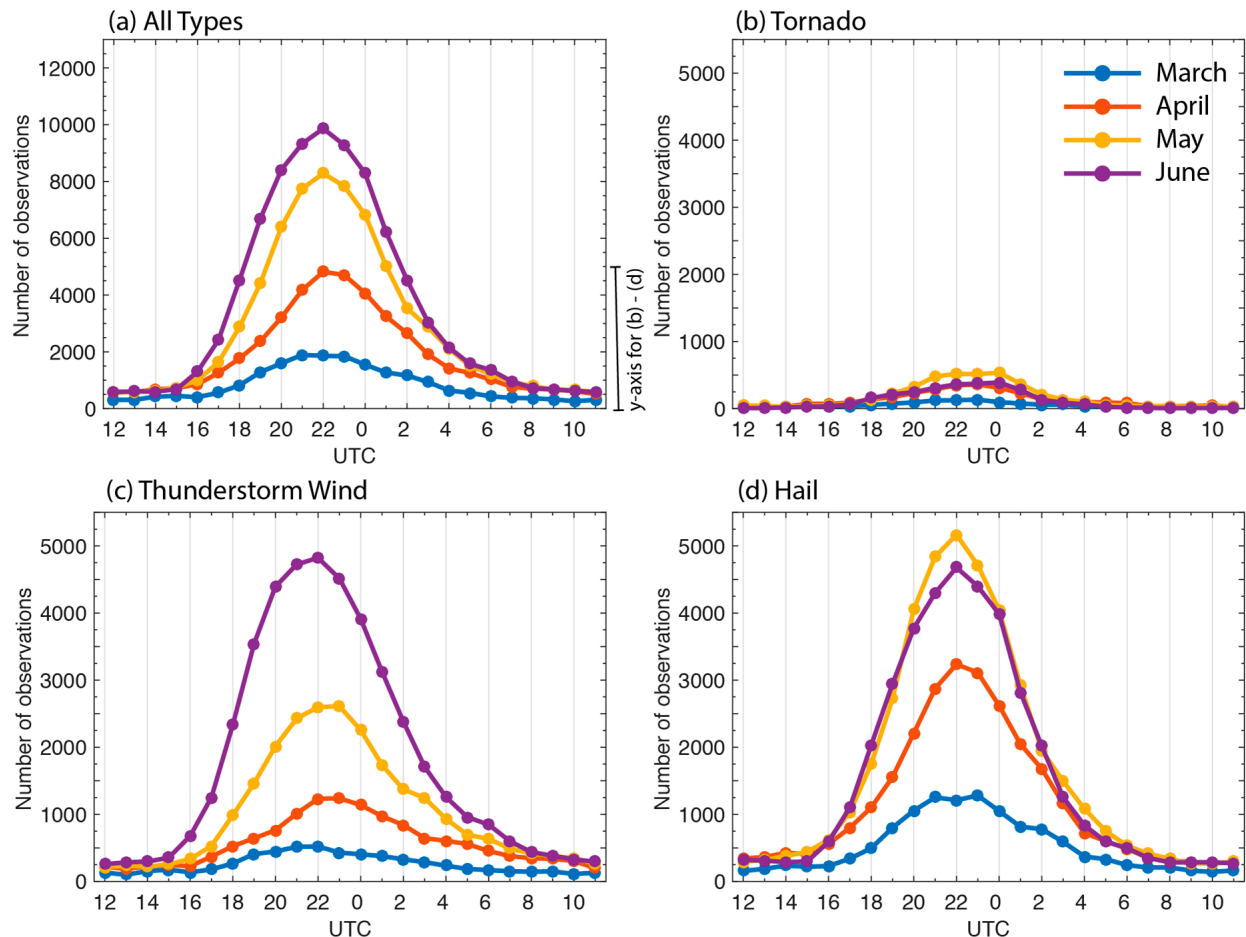


Figure 3. Diurnal variation in total monthly reports during 2001–2013 for (a) all SCW types, (b) tornado, (c) thunderstorm winds, and (d) hail. These reports represent the total events across the study domain.

3.2. Simulated SCW in Current Climate

Unless otherwise stated, the model evaluation will focus on SCW days instead of the number of SCW events. This is a compromise to the relatively low (3 hourly) frequency of the archived three-dimensional model fields that are used for computing UH. [Many commonly used 2-dimensional parameters such as the composite radar reflectivity were saved hourly, however.] Herein, we count a SCW day when at least one SCW event is detected based on the proxy in the coarsened 40 km-wide square grid over a 24 h period.

Figure 4 compares the average annual March–June accumulated SCW days from the WRF simulation to the observed counterparts. It is no surprise that great similarities in the geographical distributions exist between the observed reports (Figure 1a) and days (Figure 4a), both showing two regions of high frequency, respectively, located in the Central Great Plains and south of the Ohio River. A noticeable difference between Figures 1a and 4a is the lack of one-to-one correspondence between regional “hotspots”, implying frequent reports cannot guarantee frequent days and vice versa. Subtle differences in the

geographical distribution between the monthly SCW days (Figure 5a–d) and total reports (Figure 2) are also noticeable despite their prevalent similarities.

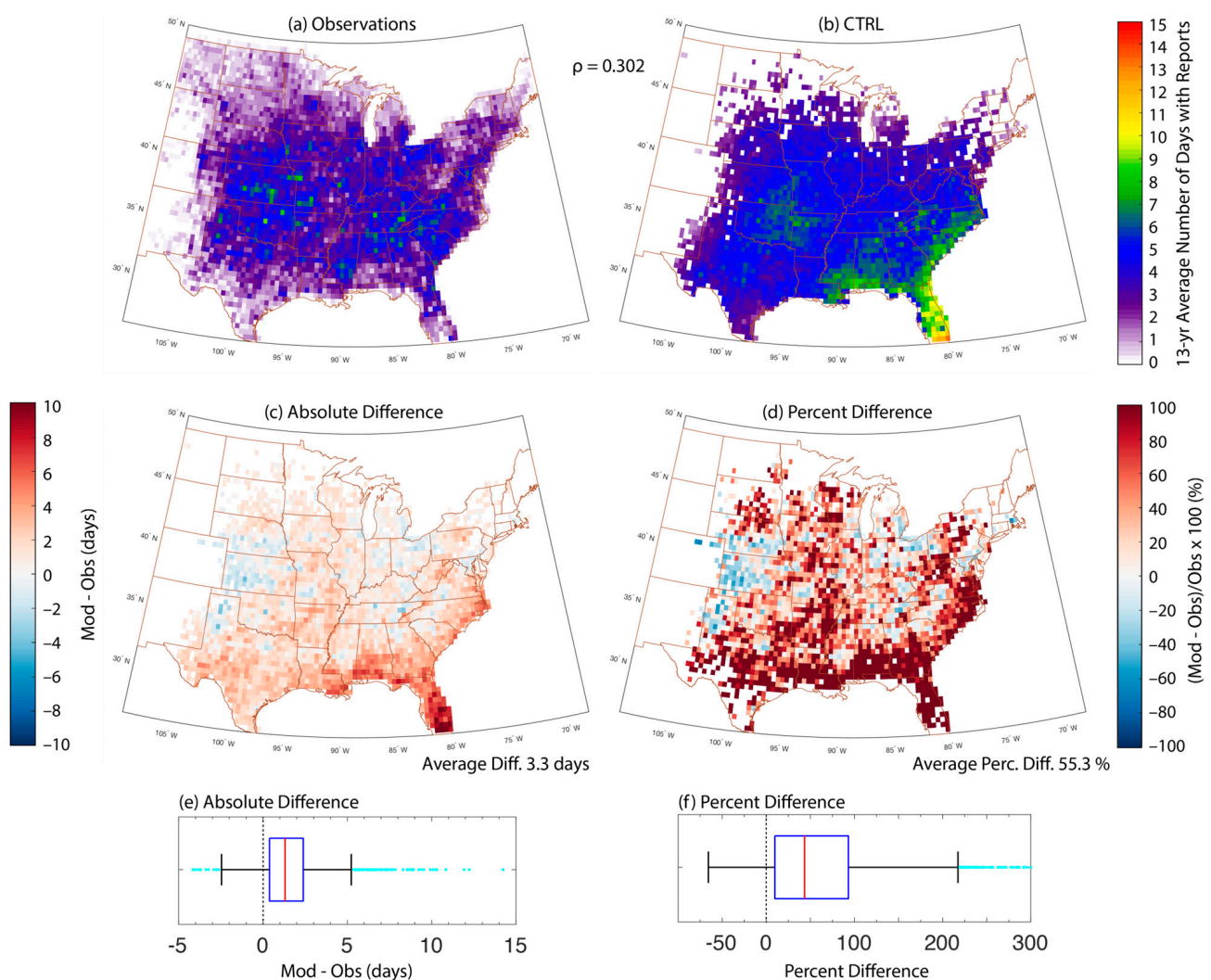


Figure 4. Comparison of 2001–2013 average number of days with SCW during March–June between (a) observations and (b) WRF simulation. (c,d) show absolute difference (WRF-OBS) and percent difference, respectively. ρ is the pattern correlation. (e,f) Box plots illustrating distribution of absolute difference and percent difference, respectively. Data points are the grid point values shown in (c,d). The edges of the box are the 1st and 3rd quartiles, and the red line is the median. Whiskers represent $\pm 2.7\sigma$. Any points outside of the whiskers (cyan dots) are outliers.

Overall, the model is able to reproduce many observed spatial characteristics. In particular, WRF roughly captures the above-discussed two predominant active regions. One apparent departure from observations is the widespread area of overestimation along the Gulf and Atlantic coast and in Florida, resultant in a low pattern correlation (0.3) over the mapped region. In addition, WRF misses some observed hotspots in the central part of the Great Plains. The areal average mean bias is 3.3 days, with the box plot in Figure 4e indicating that most of the area with the overestimation < 3 days (3rd quartile) and the extreme difference of > 5 days is associated with the bias in the Gulf and Atlantic coasts and Florida.

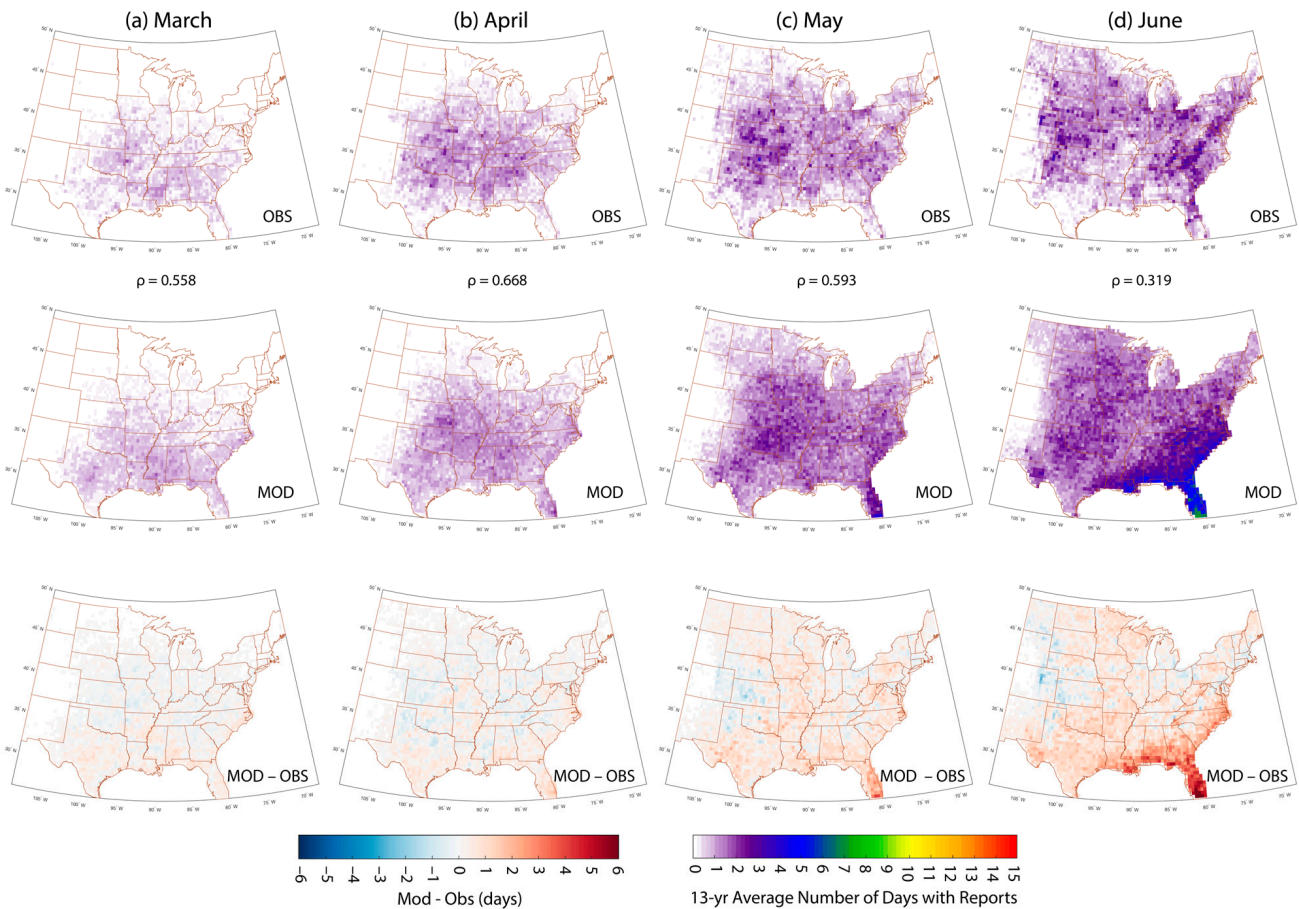


Figure 5. Thirteen-year average monthly SCW days for observations (top) and simulation (middle). Bottom panels are model biases (model-OBS). Columns (a–d) from left to right correspond to March, April, May, and June, respectively.

As illustrated in the monthly climatological distributions in Figure 5, WRF reasonably well replicates the observed poleward spread and meridional expansion of more-frequent SCW days as the season marches. The persistent increasing trend in the SCW days with the seasonal transition is also in good agreement with the observations. Many characteristic spatial features are properly simulated as indicated in the monthly pattern correlation (with an exception in June). However, the model's region of relatively high SCW days in each month does not quite go as far west as those regions shown by the observations in the central Great Plains, and as a result, the center of the high SCW days in the model appears shifted more to the east. This is responsible for the low bias in the SCW days in Kansas, Colorado, and part of the surrounding states.

The largest bias occurs along the Gulf and Atlantic coast in June, and to a lesser degree for other months; the June discrepancy accounts for more than 40% of the above-mentioned seasonal overestimate and the low pattern correlation in seasonal SCW days (Figure 4). This problem, along with the high biased precipitation along the coastal regions as indicated in [31], is likely a consequence of inland warm temperature bias, which is conducive to generating inland sea breezes that are too strong and offshore land breezes that are too weak.

The histograms of 13-year average monthly SCW days in Figure 6 further highlight the model's capability to capture the observed seasonal cycle and also the model's overproduction of severe weather occurrence for May and June. Both the absolute and percent bias amplify with the season from early spring to summer, conforming to the general concept that models are usually more skilled at simulating the cold-season weather because of the overall strong large-scale forcing during this season. [This notion may not hold if GCMs

are used to drive regional models, where regional models can improve the GCM results, particularly in warm seasons [47,48].] Furthermore, the interannual variability in terms of the standard deviation is quite comparable between the WRF simulation and observations.

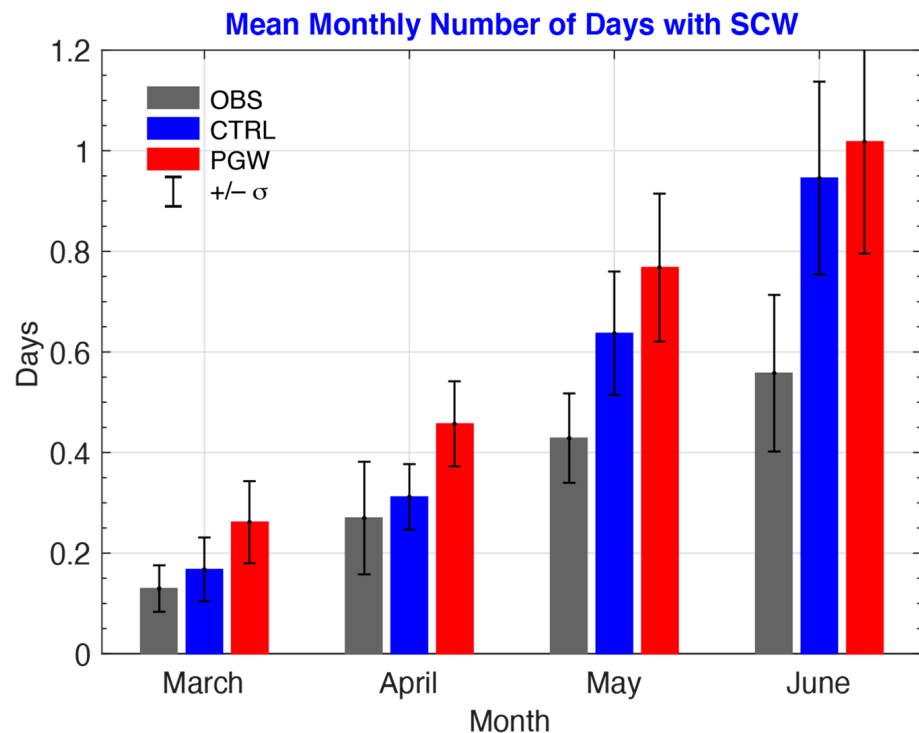


Figure 6. Thirteen-year average monthly SCW days for observation (OBS), retrospective (CTRL), and future (PGW) climate simulations. Monthly days of SCW were spatially averaged over all land points of the domain to determine spatial average monthly SCW days for each year. Then 13-year average values were computed. The error bar is $\pm$ one standard deviation from the 13-year average, indicating the year-to-year variation.

Figure 7 shows the 13-year average of the monthly diurnal cycle of SCW produced by the model in comparison to the observations. Herein, the model-based SCW is determined from the instantaneous UH/Z meeting the pair of proxy thresholds in (3) for each three-hour interval. [We did not calculate SCW occurrence at each daily hour since the 3D model fields are saved every 3 h.] The curve shown for the observation in the figure is based on the SCW reports ± 30 min from the top of the hour. The diurnal variations of severe weather are produced by the model, with the afternoon-evening timing of the maximum occurrence being roughly comparable to observations. However, the late-night suppression of severe thunderstorms is underestimated, leading to an overall weaker diurnal signal. The particularly notable discrepancy between the model and observation in early summer (Figure 7d) is attributed to the excessive SCW in the southeastern coastal regions during the nighttime (not shown) simulated by the model, possibly owing to unrealistic sea-land circulations in association with biased inland temperature as discussed above.

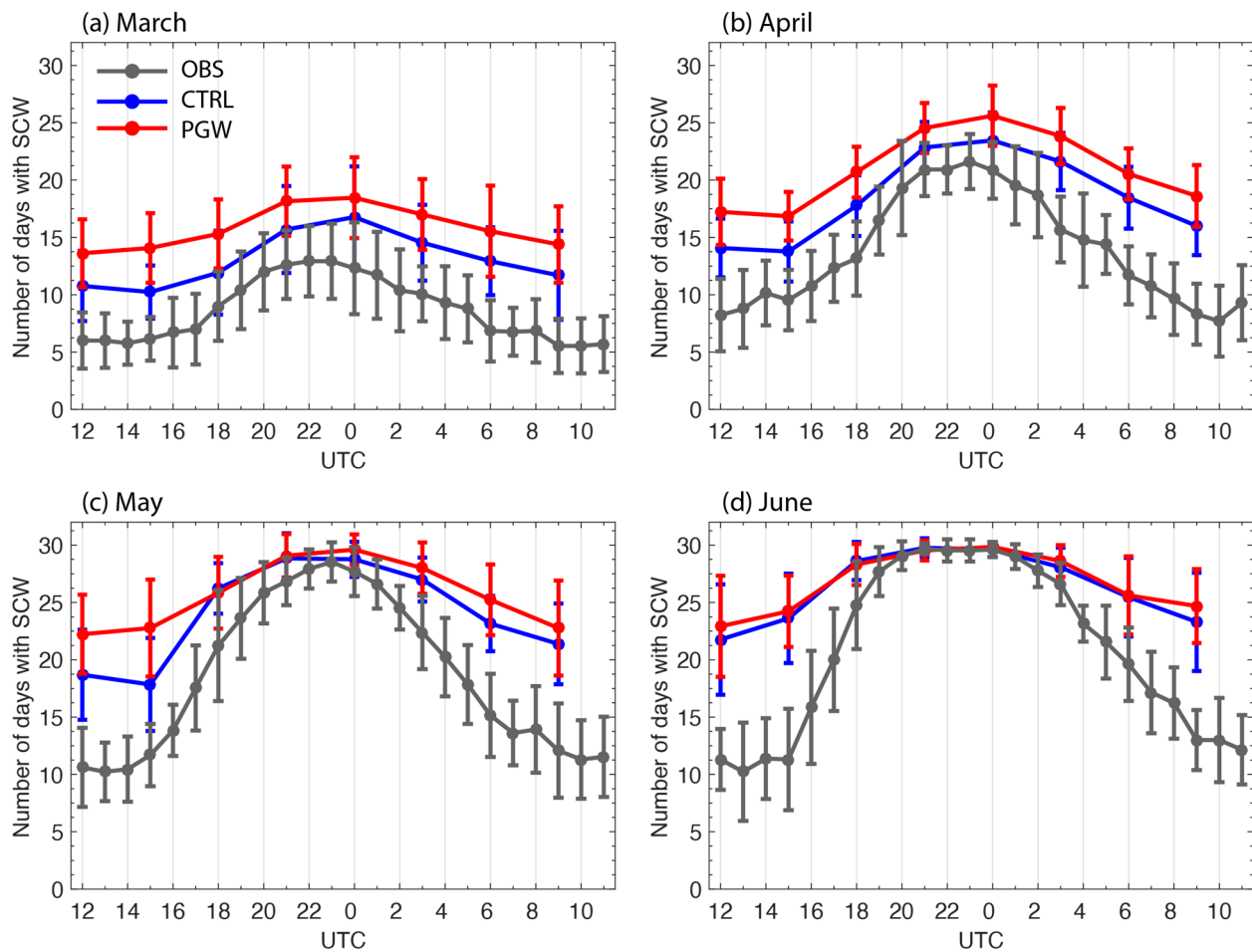


Figure 7. Diurnal cycle of SCW from observations (grey), retrospective simulation (blue), and PGW simulation (red), showing the 2001–2013 average number of monthly SCW events across all land points of the study domain. Error bars represent 1- σ from the 13-year mean.

3.3. SCW in the Pseudo-Global Warming

As aforementioned and detailed in [31], the large-scale circulation in the present day is much preserved in the pseudo-global warming; however, the environmental conditions of convective storms could still undergo changes in response to the imposed warming and moistening perturbations and thus affect the SCW activity, including its occurrence and intensity. In this section, we investigate how severe weather occurrence responds to a warmer-moister climate by comparing the retrospective simulation with the PGW simulation. As demonstrated by the seasonal frequency in Figure 8, the spatial pattern of severe thunderstorm occurrence is very comparable between the two simulations, with the active regions in the retrospective simulation (i.e., the central Plains and Southeast) being intact in the warmed climate. On the whole, however, SCW becomes more common over most of the continental area in response to the climatic warming. A weak SCW reduction is confined to Florida, as well as some scattered areas in the Northern Great Plains and along the Appalachian Mountains. The absolute change is essentially normally distributed (Figure 8e), with the domain mean absolute increase in SCW days of 2.6 days, which corresponds to a percent increase of ~23%. Moreover, SCW activity expands westward and northward. Consequently, some present SCW-free regions west of the Great Plains and in the Northeast are projected to suffer from severe weather in the future. This is revealed by the large percentage change along the Front Range that results from the current sparsity of SCW (Figure 8d).

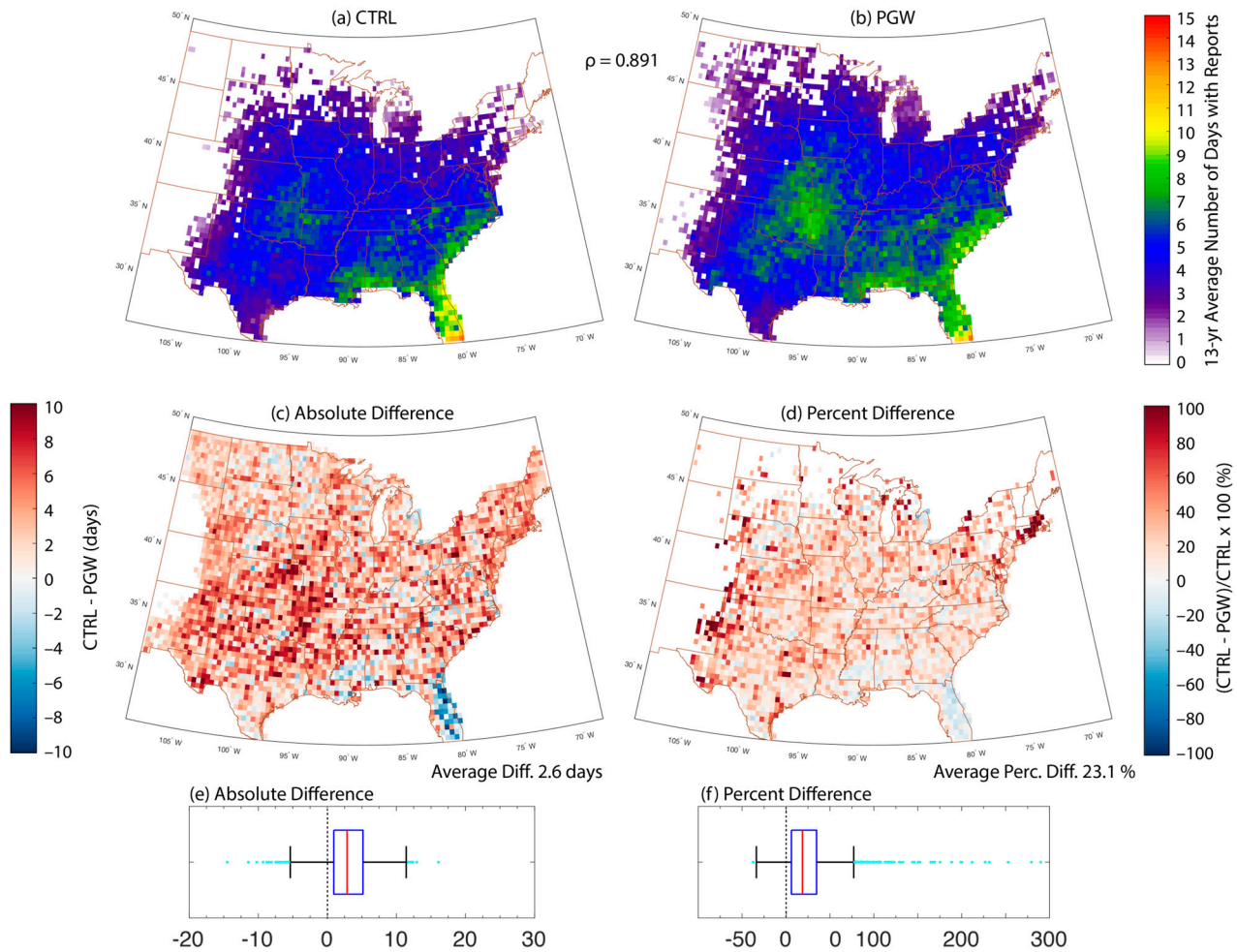


Figure 8. Comparison of 13-year average number of March–June SCW days between two simulations. (a) Retrospective simulation, (b) PGW simulation, (c) absolute difference (PGW–CTRL), and (d) percent difference. For (d), grid points with CTRL’s days with severe weather are less than 1% of total possible days are filtered out. (e,f) Box plots illustrating distribution of absolute difference and percent difference, respectively. Data points are the grid point values shown in (c,d). The edges of the box are the 1st and 3rd quartiles, and the red line is the median. Whiskers represent $\pm 2.7\sigma$. Any points outside of the whiskers (cyan dots) are outliers.

As indicated in Figure 9, the climatic warming would not alter the fundamental and robust features associated with seasonal evolution, such as the intensification of the SCW activity and expansion of the SCW impacted areas from early spring to summertime. Similar to the seasonal number of SCW days (Figure 8), the PGW simulation shows an increase in the number of SCW days and more areas subject to SCW in all months compared to the retrospective simulation, but there are some characteristic changes that take place each month. SCW enhancement is concentrated to the Ohio Valley, the South, and the Southeast, except in scattered regions of a decrease along the Gulf Coast and Florida in March. By April, the area of enhancement spreads westward, reaching almost to the Front Range. May is still dominated by an increasing trend, despite some regions of a decrease scattered south of the Ohio River. In June, significant increases are limited to the foothills of the Rocky Mountains and Northeast, but an obvious decrease of ~ 10 – 30% occurs in the Ohio Valley and other scattered areas of the Midwest. Florida experiences a weakening trend for all months.

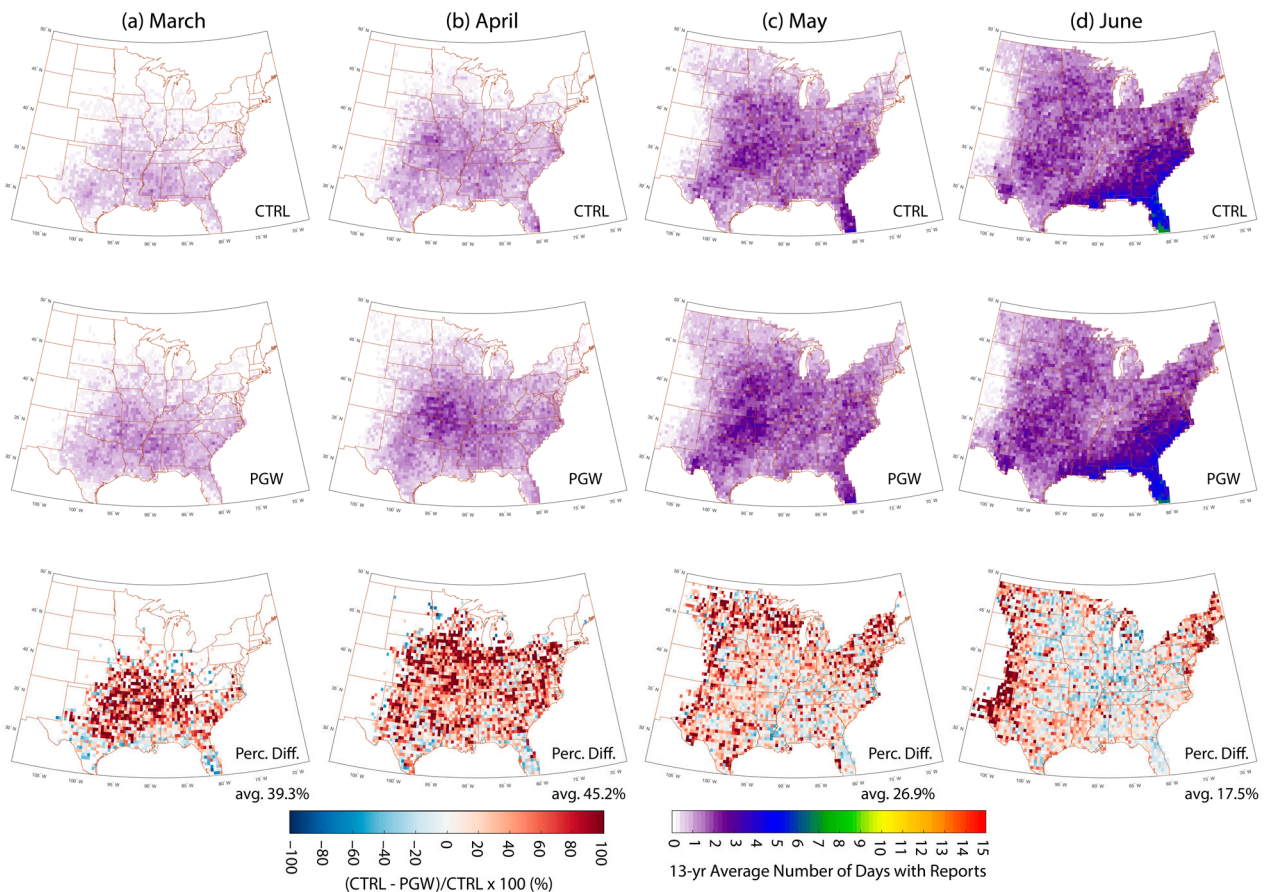


Figure 9. Thirteen-year average monthly SCW days for CTRL (top) and PGW (middle). Bottom panels are percent differences between two climates (PGW-CTRL). Columns (a–d) from left to right correspond to March, April, May, and June, respectively.

The comparison of 13-year mean monthly SCW days over the domain between CTRL and PGW simulations (Figure 6, blue and red bars) further illustrates sub-seasonal variations in the climate-impact change signal, showing a steady increase (in the difference) that peaks in middle-to-late spring and a subsequent transition to a less enhanced increase in June. The mean absolute change is 0.09, 0.15, 0.13, and 0.07 days in March, April, May, and June, respectively, and the percentage difference is 56, 47, 21, and 8%, declining with the seasonal progress. These results suggest that although averaged over the domain, the SCW is on an increasing trend, regional dependencies exist, and the climate change may substantially enhance SCW activity in the early-middle springtime in most areas but slightly weaken the occurrence in the summertime in the Midwest down to the Southeast.

In general, the diurnal patterns are not sensitive to the climate warming, characterized by similar timings for both the daily maximum and minimum for the two climates (Figure 7). One noticeable sub-seasonal variability is the nearly constant increment throughout the diurnal hours in March and April, while May and June feature relatively greater increases in late night and early morning than in other times, leading to a reduced diurnal signal.

It is generally believed that the greater the UH/Z values, the more severe thunderstorms. Therefore, their magnitude changes would provide information about how SCW intensity may respond to climate warming as well as the above-presented frequency increase. Figure 10 shows the distribution of extreme grid-point reflectivity at 00 UTC from 2001 to 2013 that exceeds the 95th percentile reflectivity. The 00 UTC time is exemplified because this time is close to the diurnal peak occurrence of SCW (Figure 7). The figure displays a decrease in relatively weak reflectivity bins but a substantial increase in high reflectivity ranges (by 50% or more; inset in Figure 10) for all months, suggestive of an increase in SCW severity in the warmer climate. Such results are consistent with an earlier

study by [40], where it was shown that a warmer climate shifts the convective population with fewer weak-to-moderate convection and more extremely strong convection. The differences in UH are generally negligible (not shown).

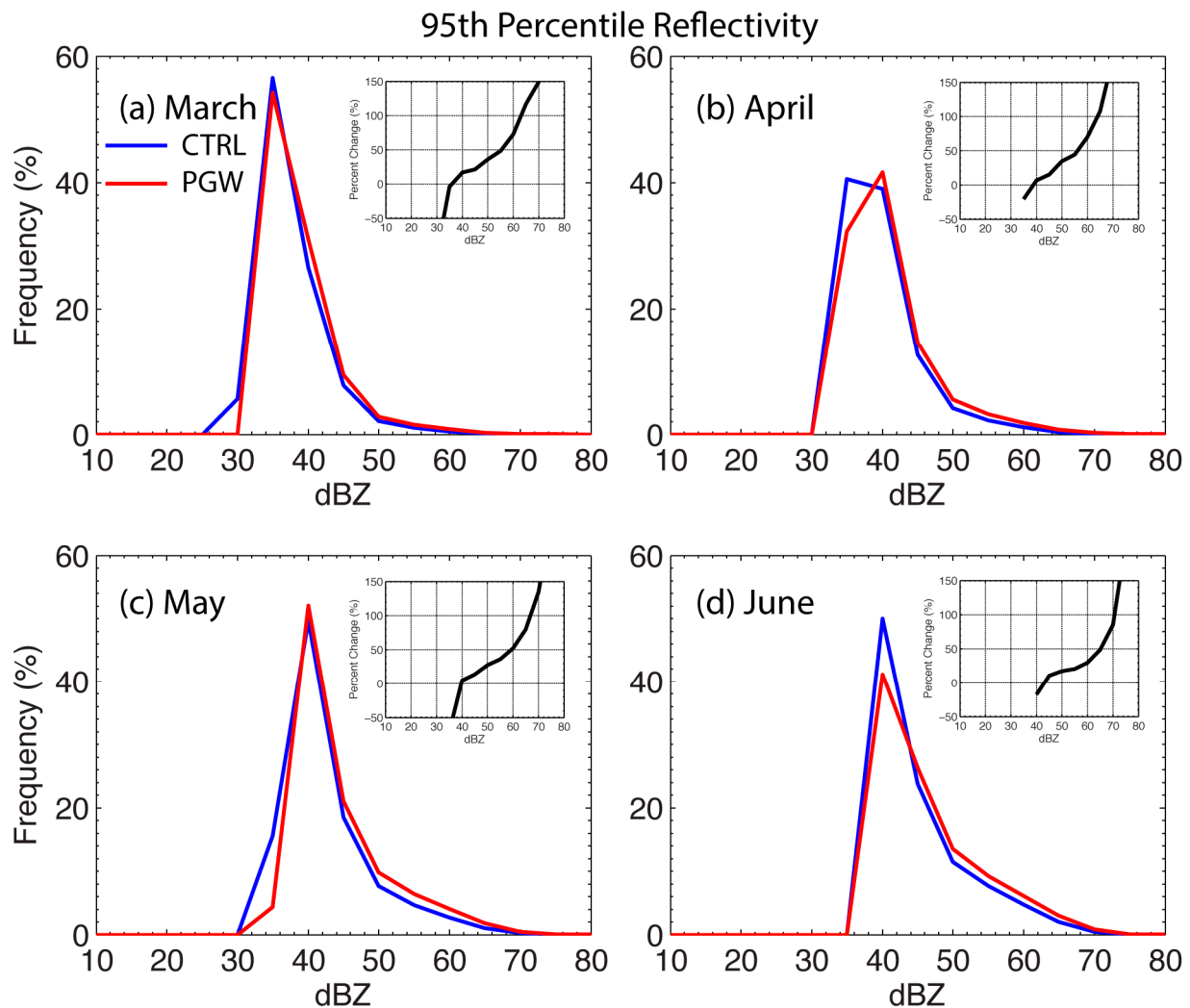


Figure 10. Frequency distribution of the grid-cell reflectivity values at 00 UTC model valid time averaged over all land points of the domain from 2001 to 2013 that exceed the 95th percentile value based on each of the CTRL and PGW simulations. Insets show the percent change in occurrence of each reflectivity range. The width of the distribution bin is 5 dBZ. The frequency is with respect to the 95th percentile events.

3.4. Environmental Conditions

The storm initiation and intensity are determined by its environmental conditions. Many dynamic and thermodynamic indices have been developed in the operational and research communities to characterize the large-scale environment conducive to severe thunderstorm development. Among the variety of meteorological parameters, two bulk variables, the vertical shear of horizontal wind between the surface and 6 km altitude (S06) and the CAPE, as well as their combination as reviewed in the introduction, have been often used to predict the occurrence of severe storms and are examined here to quantify environment changes behind the above-presented SCW changes. The probability distribution of S06 and CAPE in Figures 11 and 12 corresponds to the 00 UTC conditions when SCW is most active. A rather small difference in S06 as evinced by the almost overlapped curves in Figure 12 is consistent with and attributed to a weak wind perturbation imposed on the PGW conditions based on Equation (2). The climate perturbation was typically less

than 1 m s^{-1} across most of the model domain in spring and summer from the 19 ensemble CMIP5 models used in [31] [see Figures 1 and 2 in [31]]. In contrast, large differences in CAPE show evidence of the increasing frequency in the high instability range (i.e., $\text{CAPE} > 1000 \text{ J kg}^{-1}$) in a warmed climate, favorable for the occurrence of severe storms (Figure 11). As reported in [40], the increase in CAPE is mostly ascribed to the water vapor increase in accordance with the Clausius–Clapeyron relation, with little contribution from changes in the lapse rate. Moreover, an attendant increase in convective inhibition (CIN) prohibits weak convection but allows the thermodynamic instability buildup to extreme levels for severe convection. Taken together, the warmed climate features a dominant impact of thermodynamic changes versus dynamic changes for the convective environment.

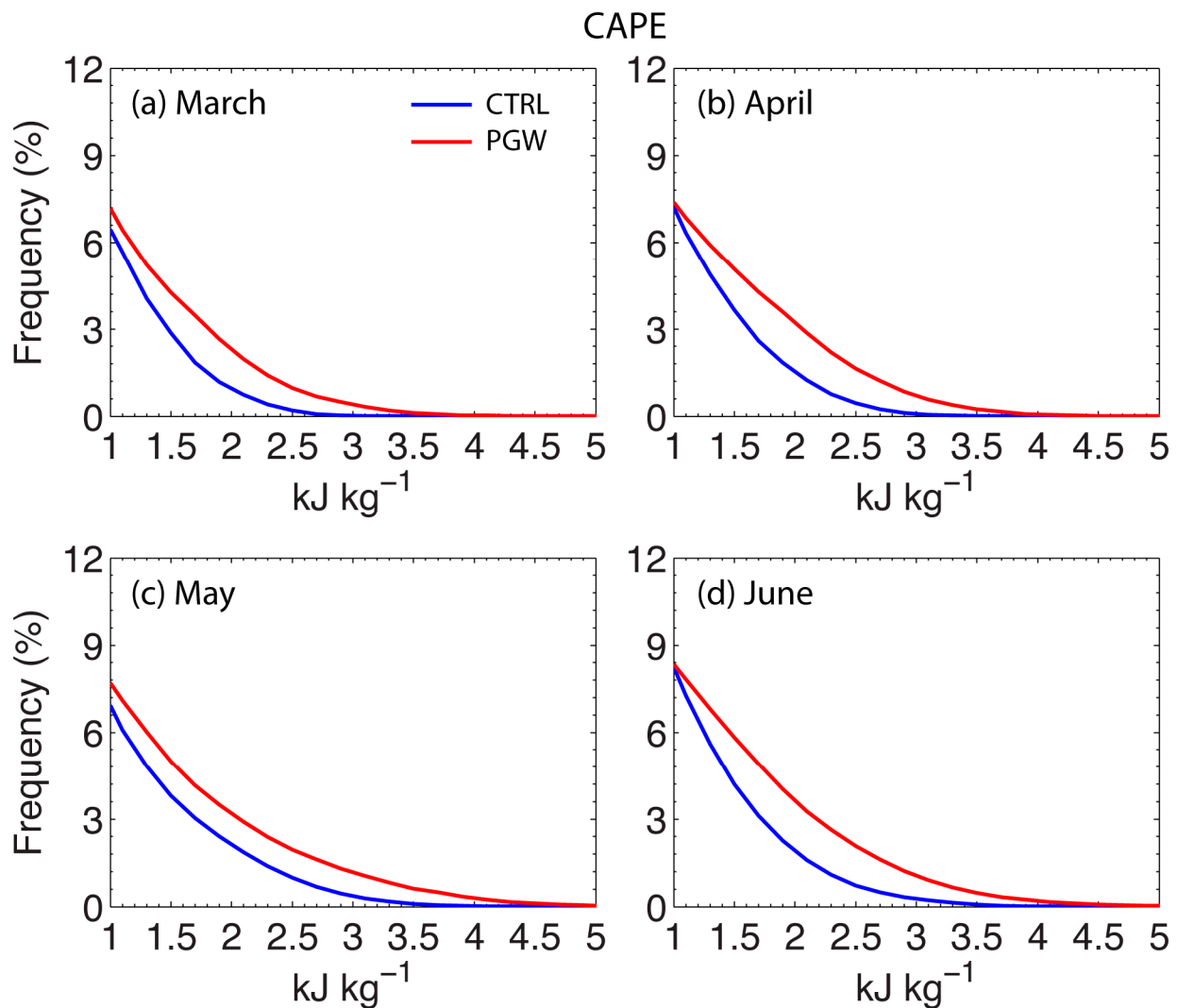


Figure 11. Comparison of frequency of grid-cell CAPE values between CTRL (blue) and PGW (red) from 00 UTC model result averaged over all land points of the domain and from 2001 to 2013. (a–d) correspond to March, April, May, and June, respectively.

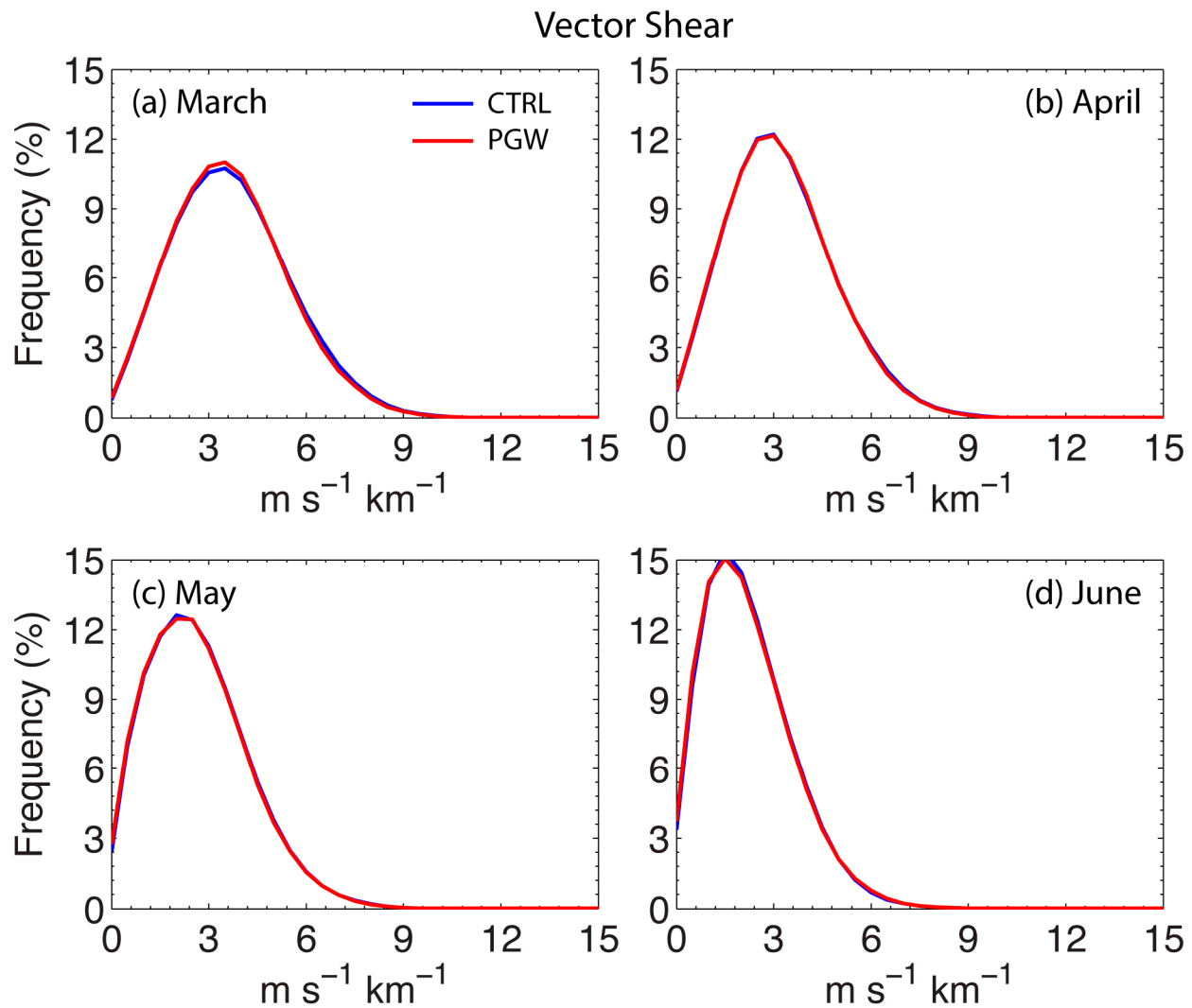


Figure 12. Same as Figure 11 but for 0–6 km shear. (a–d) correspond to March, April, May, and June, respectively.

3.5. Discussion

SCW in the United States has been previously investigated in the context of regional climate modeling at convection-permitting grid resolution. [18] explored its regional climatology and variability via a 10-year March–June WRF-model simulation at grid spacing of 4.25 km from a reanalysis dataset driven daily (24 h long). [19] conducted a 10-year March–May sequence of GCM forced continuous seasonal WRF integrations at a grid spacing of 4 km. Both studies showed that high-resolution downscaling produced fairly realistic spatial and temporal distributions of SCW. Although the horizontal grid spacings are comparable, one important difference between our simulation and these prior modeling studies is that the continuous 13-year integration over a continental-scale domain allows a better handling of soil moisture and temperature spinup and long-memory processes. The reasonable replication of the historical observations lends further support for the application of convection-permitting downscaling to understand the observed SCW climatology and assess the potential changes in a future warmed world.

Ref. [20] conducted a GCM-driven convection-permitting downscaling of 2080–2090 springtime SCW under a business-as-usual emissions scenario. The documented seasonal variations relative to a historical period (1980–90) mirror those from our PGW projections, ranging from a statistically significant increase in March to a slightly increase in April and to a minimal change in May. However, their reported SCW increase is largely confined

to the Middle Mississippi, Lower Mississippi, Ohio, and Tennessee valleys, whereas our projections show enhanced spring SCW activity almost across the entire Central and Eastern U.S., with the highest percentage increase along the foothills of the Rocky Mountains and high latitudes of the model domain. Even though most of the differences could result from the usage of different WRF-model forcing between the two studies, the interpretation is complicated by the different SCW indices examined, namely SCW events in [19,20] and SCW days in this study. More recently, [21] examined the potential impact of climate change on SCW through a succession of daily initialized 4 km WRF model downscaled simulations of GFDL CM3 under historical (1971–2000) and RCP8.5 (2071–2100) conditions. In the study, synthetic SCW day climatologies are created using upward vertical velocity exceeding 22 m s^{-1} as a proxy for SCW occurrence. Their results show an increase in SCW occurrence and a longer severe weather season by the end of the 21st century, similar to the findings in our PGW projection. Unlike the current work focusing on the spring and early-summer only, however, [21] investigated the SCW occurrence in all seasons, as well as the distinct downscaling approaches and the different SCW model proxy.

The enhanced SCW activity in the PGW simulation is a consequence of the widespread intensification of convective instability in connection with the water vapor increase. In particular, the westward and northward shift in SCW activity closely follows the geographical maximum increase in CAPE, and the large April–May SCW enhancement is generally in good correspondence with the seasonal maximum increase in CAPE during that period (not shown). It should be pointed out that the enlarged thermodynamic instability would promote not only the occurrence of severe thunderstorms but also the potential for enhanced severity. Distinct from the prevalent increase in CAPE, the vertical wind shear, a well-known dynamical factor for convective organization, displays little change because of the weak perturbation in large-scale dynamics added to the initial and boundary conditions in the PGW simulation. This contrasting thermodynamic vs. dynamic response to climatic warming is generally in agreement with some existing research for the change of severe thunderstorm environments. For example, [17] examined downscaled GCM projections with a 25 km regional model, and [15] analyzed one CMIP5 ensemble; both reported a robust future increase in the occurrence of favorable severe thunderstorm environmental conditions characterized by the daily CAPE-S06 distribution shifting toward increasing occurrence of high CAPE. A similar finding from GCM projections of high warming scenarios was documented for Australian severe thunderstorm environments by [14], demonstrating a significant increase in the frequency of severe thunderstorm environments for Northern and Eastern Australia due to increasing CAPE from higher continental moisture, despite decreases in the frequency of environments with high vertical wind shear.

Advantages of convection-permitting high-resolution models over coarse-resolution regional and global models have been discussed in many previous studies (e.g., [30]). However, the grid spacing that was recently used frequently (i.e., $\sim 4 \text{ km}$) in the regional climate modeling community capably resolves convective storms but is unable to explicitly resolve all of the attendant severe weather phenomena. Therefore, a SCW model proxy such as the paired Z/UH thresholds used here is necessary for SCW detection. Despite the great success in predicting major observed climatological features by the use of such a proxy, this simple approach has limitations because of the subjective selection of the model dependent threshold magnitudes. Moreover, in the real world, the UH/Z thresholds could vary geographically and seasonally without a universal constant.

The future SCW activity in this study is assessed from a warmer end-of-century simulation, in which the same initial and boundary conditions as the historical simulation are perturbed with the mean climate warming from the CMIP5 model ensemble. In comparison with the traditional downscaling approach with boundary conditions being provided from a single GCM run, our PGW approach has several merits. First, the imposed climate perturbation represents the difference between two CMIP5 model ensemble mean climates and thus is free of the systematic GCM biases. Second, the multi-model ensemble mean forcing minimizes the influence of unforced natural climate variations [49], thus representative of

the best estimate of the GHG forced climate change and the more deterministic first-order thermodynamic component of increased GHG forcing. Finally, the PGW technique makes it possible to compare directly between a current year and the corresponding “future” (PGW) year in the context of interannual variability. However, the PGW simulation does not incorporate the more uncertain dynamical or storm-track changes, which might have non-negligible impacts on the SCW frequency and intensity. Note that even though the multi-model ensemble mean dynamic signal is weak, as indicated in [31], the dynamic component may be important for each ensemble member due in part to internal or natural variations. Even with this limitation, the PGW approach is able to represent many of the predictable physical processes of GHG forced climate change and is validated by the existing GCM-based studies of thunderstorm-favorable environments, which suggest the dominant contribution of the thermodynamic component over the dynamical component to the entire climate change signal.

4. Conclusions

This study examined the SCW climatological characters in spring and early summer in current and future warmer climate based on a pair of 13-year continental-scale convection-permitting WRF simulations, which were conducted using (1) the ERA-Interim reanalysis and (2) the reanalysis plus CMIP5 projected climate perturbations for the RCP8.5 scenario. A pair of thresholds for vertical updraft helicity and simulated composite radar reflectivity were applied to derive a model proxy to identify SCW occurrence in the simulations. The retrospective simulation was evaluated against the storm report database from the NOAA Storm Prediction Center. The comparison between the two simulations assessed the SCW response to climate warming. The primary results are as follows:

The retrospective simulation captures successfully many climatological characteristics of sub-seasonal and seasonal geographical distributions and evolution, such as the spatial spreading toward higher latitudes and the foothills of the Rocky Mountains from early spring to summer, as well as diurnal evolution, including the timing of the peak daily SCW. An exception is the excessive prediction of SCW events in the southeastern coastal regions.

In a warmer-moister future, most regions experience a seasonal increase in the SCW frequency, most notable in the foothills east of the Rocky Mountains and Northeast. In addition, the SCW changes are seasonally dependent, with the largest percentage increase occurring in the early-middle spring.

Environmental conditions feature a significant increase in CAPE but minimal changes in the deep tropospheric shear in the warmed climate.

More SCW in the future could reach extreme levels in association with enhanced convective severity in response to dominant thermodynamic instability changes.

The current study investigates the SCW in the Central and Eastern United States by performing convection-permitting dynamical downscaling for both the historical and future climate, where the future climate simulation is based on a pseudo global warming approach, taking advantage of the fact that projected temperature and moisture changes by global climate models are relatively robust from model to model. The usage of very high resolution is shown to provide promising estimates of the SCW occurrence in the historical climate as a result of resolving the mesoscale convective processes, and thus the estimate for future SCW climatological attributes in a warmer-moister climate is viewed with relatively high confidence. Regardless, the impact of sub-monthly dynamical changes and synoptic storm changes is missing in the future climate simulation. Future work will extend the current study to full climate change simulations based on a new bias-correction approach [50] and confirm whether the present findings hold when large-scale dynamical changes are allowed.

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