Estimations of Hazardous Convective Weather in the United States Using Dynamical Downscaling

VITTORIO A. GENSINI

Meteorology Program, College of DuPage, Glen Ellyn, Illinois

THOMAS L. MOTE

Climatology Research Laboratory, Department of Geography, University of Georgia, Athens, Georgia

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ABSTRACT

High-resolution (4 km; hourly) regional climate modeling is utilized to resolve March–May hazardous convective weather east of the U.S. Continental Divide for a historical climate period (1980–90). A hazardous convective weather model proxy is used to depict occurrences of tornadoes, damaging thunderstorm wind gusts, and large hail at hourly intervals during the period of record. Through dynamical downscaling, the regional climate model does an admirable job of replicating the seasonal spatial shifts of hazardous convective weather occurrence during the months examined. Additionally, the interannual variability and diurnal progression of observed severe weather reports closely mimic cycles produced by the regional model. While this methodology has been tested in previous research, this is the first study to use coarse-resolution global climate model data to force a high-resolution regional model with continuous seasonal integration in the United States for purposes of resolving severe convection. Overall, it is recommended that dynamical downscaling play an integral role in measuring climatological distributions of severe weather, both in historical and future climates.

1. Introduction

Preliminary research suggests that environmental controls related to hazardous convective weather (HCW; tornadoes, severe wind gusts, and large hail) will increase in response to elevated greenhouse forcing (Del Genio et al. 2007; Trapp et al. 2007a, 2009; Van Klooster and Roebber 2009; Gensini et al. 2013; Diffenbaugh et al. 2013). Despite this evidence, climate change assessments have largely avoided any conclusions regarding potential changes of HCW in a future climate [see discussions in Alley et al. (2007), Karl et al. (2009), and Brooks (2013)]. This is primarily due to problems with the historical record of observed HCW reports, the link between HCW reports and associated environmental controls, and the large spatial scale at which global climate models (GCMs) operate relative to HCW.

The widely used Community Climate System Model version 3 (CCSM3; Collins et al. 2006) GCM is a spectral model with 85-wavenumber triangular truncation (approximately 1.4° resolution at the equator) in the horizontal (Collins et al. 2006). This GCM configuration translates roughly to a 150-km horizontal grid spacing in the central United States, whereas explicit resolution of convection should be done at a horizontal grid scale of less than or equal to 4 km (Weisman et al. 1997). Therefore, the resolution of typical GCM output lacks the ability to resolve HCW. The current understanding of potential changes in future HCW regimes is limited to environmental controls. While more HCW environments could mean more events in the future, such environments are periods when the atmosphere is favorable for organized HCW, not that it will necessarily occur.

Recent exploratory research has indicated that dynamical downscaling of GCM data has become possible owing to enhanced model microphysics schemes, increases in computer processing speed, and new GCM data availability (e.g., Trapp et al. 2011; Robinson et al. 2013; Mahoney et al. 2013). Thus, the purpose of this research is to utilize dynamical downscaling to explicitly resolve proxy HCW events using GCM input data. Specifically, this manuscript will examine a GCM historical

Corresponding author address: Vittorio A. Gensini, Meteorology Program, College of DuPage, 425 Fawell Blvd., Glen Ellyn, IL 60137.
E-mail: gensiniv@cod.edu

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period (1980–90) driven via reanalysis in relation to observed HCW reports. This historical baseline will provide a comparison for future period simulations and bias correction estimates.

2. Background

Dynamical downscaling is a method for obtaining high-resolution climate information from relatively coarse-resolution GCM output. Using dynamical downscaling, recent research indicates it is now practical to downscale GCM-scale output to the 4-km grid spacing (Trapp et al. 2007b; Trapp et al. 2011; Robinson et al. 2013) required for resolving deep convective processes (Weisman et al. 1997). In fact, a recent study has explored the use of dynamical downscaling at a spatial resolution of 1.5 km (Kendon et al. 2012), while several other studies have performed seasonal downscaling at or below 3 km (e.g., Hohenegger et al. 2008; Sato et al. 2009; Langhans et al. 2013; Warrach-Sagi et al. 2013; Prein et al. 2013). Generally, these studies all found utility in the increased spatial resolution provided by dynamical downscaling for their respective research. For severe convection, dynamically downscaled global reanalysis data [similar to the coarse resolution of many GCMs ($\sim$100 km)] have accurately represented HCW during the peak of the convective season (May–June; Trapp et al. 2011; Robinson et al. 2013). However, no studies have examined the use of dynamical downscaling on historical GCM output for HCW purposes in the United States.

It is important to note that despite a significant increase in HCW reports over the last three decades, research indicates that environmental controls factors [i.e., convective available potential energy (CAPE) and 0–6-km shear; Gensini and Ashley 2011; Robinson et al. 2013] and modeled proxy reports (Robinson et al. 2013) have exhibited little to no trend. This recent inflation in HCW reports has been extensively documented (Doswell and Burgess 1988; Grazulis 1993; Brooks and Doswell 2001, 2002; Verbout et al. 2006; Doswell 2007). Thus, the recent increase in losses from severe thunderstorms (Changnon 2001) and tornadoes (Brooks and Doswell 2001; Changnon 2009) can be attributed to societal and economic changes rather than an increase in event frequency (Bouwer 2011).

3. Methodology

Using 1980–90 historical data from the CCSM3, a HCW proxy is gridded and summed to create a spatiotemporal climatology for the months March–May. The proxy used in this research will follow that used in Trapp et al. (2011), using hourly thresholds of updraft helicity (UH) and simulated composite radar reflectivity (Z) as described by Kain et al. (2008). UH and Z data are obtained from CCSM3 data by dynamical downscaling, using the nonhydrostatic Advanced Research core of the Weather Research and Forecasting (WRF-ARW) Model (hereinafter "WRF"; Skamarock et al. 2008,). Modeled proxy HCW reports are compared to observed HCW reports over the same period using report data obtained from the Storm Prediction Center (SPC) as compiled for the National Climatic Data Center (NCDC) publication *Storm Data*. Although there are documented problems with using *Storm Data* for convective research purposes (Doswell and Burgess 1988; Brooks 2004), it is currently the most comprehensive source for HCW climatological information.

a. Region

The study region for this research encompasses all points in the United States east of the Continental Divide. This domain is centered on the central Great Plains region, which is characterized by the largest HCW frequency on Earth (Brooks et al. 2003b). While it would be ideal to include the entire United States in such a study, one must weigh the computational expense of modeling at such a high spatial resolution against the expected benefit of the results. Given that HCW rarely happens west of the Continental Divide (Brooks et al. 2003a,b; Gensini and Ashley 2011), this region has been omitted.

b. Model diagnostics

1) Parent GCM characteristics

The CCSM3 is a coupled global climate model consisting of atmosphere, land surface, sea ice, and ocean components (Collins et al. 2006). Available data include a control run (no changes in external climate forcing), a twentieth-century simulation (containing the observed changes of greenhouse gases, sulfate aerosols, volcanic aerosols, and solar irradiance from the twentieth century), and twenty-first-century scenarios (containing estimated changes in greenhouse gas concentration and aerosol concentrations). For this particular study, 11 years (1980–90) of a simulation initialized in 1870 and run through the twentieth century (the CCSM3 b30.030e dataset) was chosen in an effort to assess CCSM3 bias and error relative to actual HCW reports over the same period.

2) Regional climate model

As previously mentioned, the regional climate model (RCM) used for dynamical downscaling in this study is WRF-ARW (Skamarock et al. 2008). Initial conditions for WRF are provided from CCSM3 at 0000 UTC 1 March of each year, and integrated over a 3-month period, providing CCSM3 boundary conditions every 6 h.

TABLE 1. Relevant regional model configuration information.

Parameterization	
Microphysics	WSM6 (Hong and Lim 2006)
Shortwave radiation	Dudhia (Dudhia 1989)
Longwave radiation	RRTM (Mlawer et al. 1997; Iacono et al. 2000)
Land surface model	Noah (Chen and Dudhia 2001)
Planetary boundary layer	MYJ (Mellor and Yamada 1982)
Model parameters	
Time step	24 s
Vertical levels	35
Horizontal grid point spacing	4 km
Initial/boundary conditions	
Temperature, specific humidity, geopotential height, u and v wind, surface pressure	Surface, 27 isobaric levels; 6-h intervals
Soil temperature, soil moisture	0–10, 10–40, 40–100, 100–200 cm; 6-h intervals

Parameterizations of physical processes (Table 1) and other aspects of the regional climate model configuration are based on WRF simulations of HCW in the United States (e.g., Weisman et al. 2008; Kain et al. 2006; Trapp et al. 2011; Robinson et al. 2013). The first 6 h of the simulation are discarded, in addition to the first six lateral-edge domain points, to account for model spinup (Skamarock 2004). Since a cold start is initialized on 1 March of every HCW season, interannual soil moisture memory is lost, despite the ability to capture seasonal soil moisture feedbacks.

Nine pairs of UH/Z values were tested using fractional gross error (F_E) and mean bias (MB) statistics to determine the most appropriate threshold for HCW proxy occurrence (Fig. 1). This analysis suggests the optimal proxy for a HCW event occurs when an hourly model grid point exceeds Z values ≥40 dBZ juxtaposed with UH values ≥60 m^2 s^{-2}. This threshold depicts a relative minimum in F_E but does display a slight positive bias, which changes through the analyzed months. This threshold is slightly different than the 50–40 Z/UH pair used in previous research (Trapp et al. 2011; Robinson et al. 2013). This difference is subtle, considering the differing WRF initial and boundary conditions [National Centers for Environmental Prediction (NCEP)–National Center for Atmospheric Research (NCAR) global reanalysis rather than CCSM3] and the examination of an earlier period in the annual convective cycle (March–May rather than April–June). The slightly lower Z, but higher UH, values used in our study makes

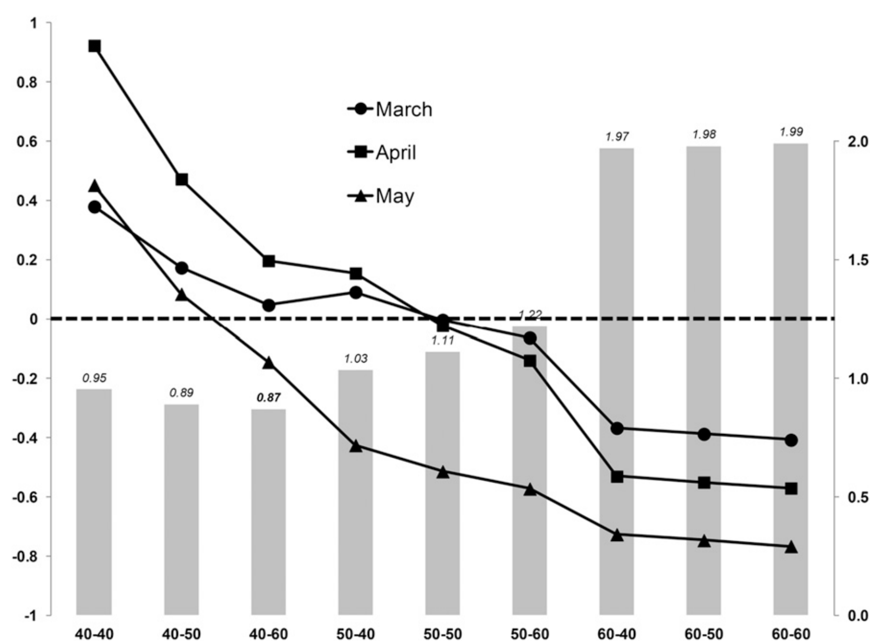

FIG. 1. Fractional gross error (gray bars; axis right) and mean bias (lines; axis left) by month for nine Z/UH pairs examined in this study.

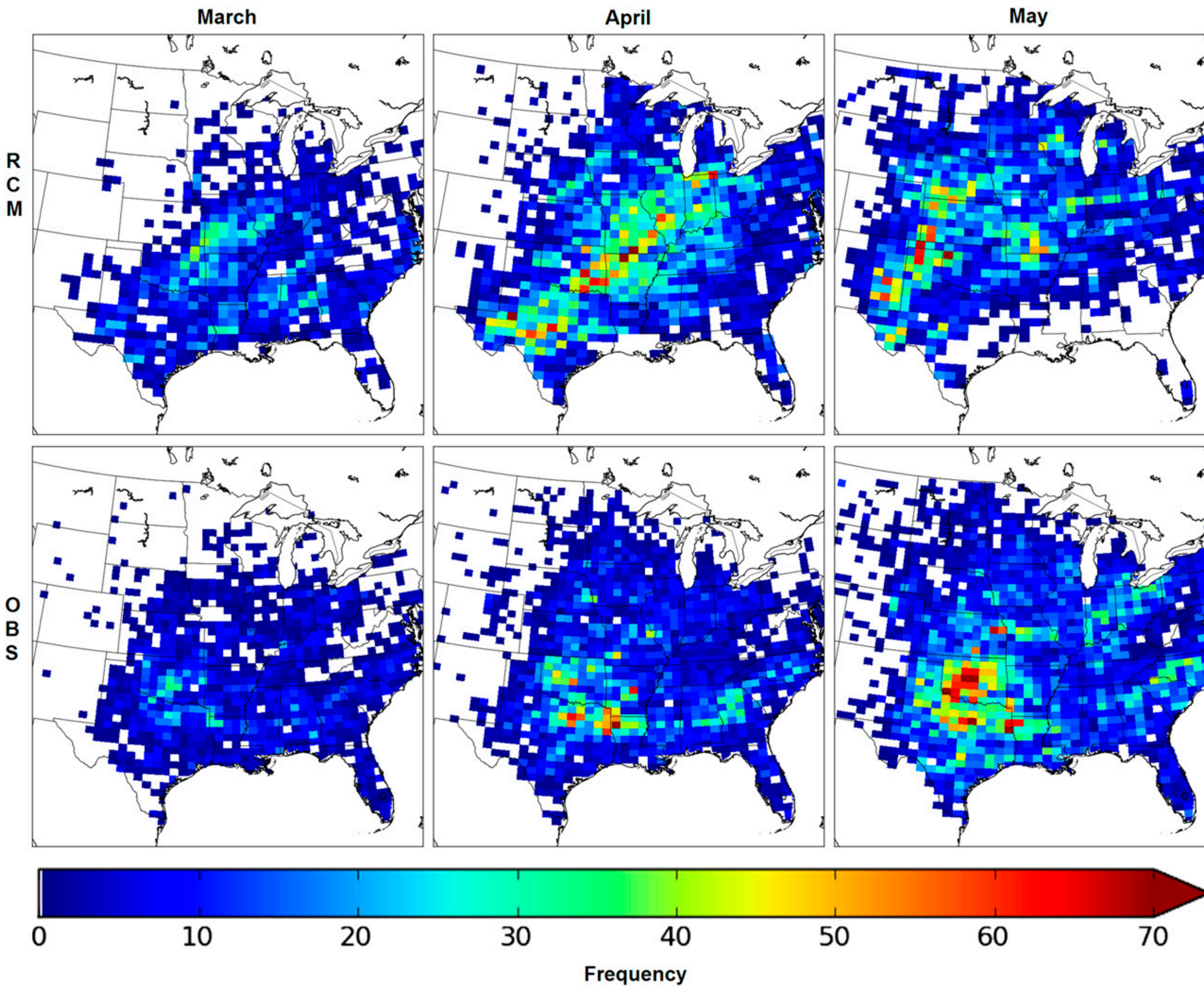

FIG. 2. Frequency of 1980–90 March–May HCW as depicted by a RCM and observations. Plot region corresponds to the simulation domain.

physical sense as earlier months in the annual convective cycle are typically dominated by a low-CAPE and high-shear environment (Brooks et al. 2007) that are strongly synoptically forced (Galway and Pearson 1981).

Although the RCM configuration, study months, and proxy report methodology are similar to previous research (Trapp et al. 2011; Robinson et al. 2013), there is an important difference to note. This study employs a longer (continuous) integration time over the entire 3-month period, which is different than the 24-h reinitialization used in Trapp et al. (2011) and Robinson et al. (2013). This longer integration time is desirable in climate modeling as it supports a better representation of influences associated with longer-memory processes (e.g., soil moisture) on HCW.

A 50-km fishnet grid was used to evaluate observed and model-simulated HCW events. This grid length is smaller than the ~80 km used in previous severe weather report climatologies (e.g., Brooks et al. 2003a) but greater than the ~38-km grid length used in a similar downscaling study (Trapp et al. 2011). This coarsened grid scale helps compensate for errors in the spatial location of observed HCW reports, and their interpolation to the nearest 4-km RCM grid point.

4. Results

Model-simulated HCW reports closely mimic the spatial evolution of observed reports for the months analyzed (Fig. 2). That is, the RCM reflects an increase in reports and a gradual northward progression of relative maxima consistent with the observed cycle of HCW during this period. These results are consistent with previous downscaling studies that examined April–June (Trapp et al. 2011). In terms of magnitude, March shows little bias relative to observations, whereas April (May)

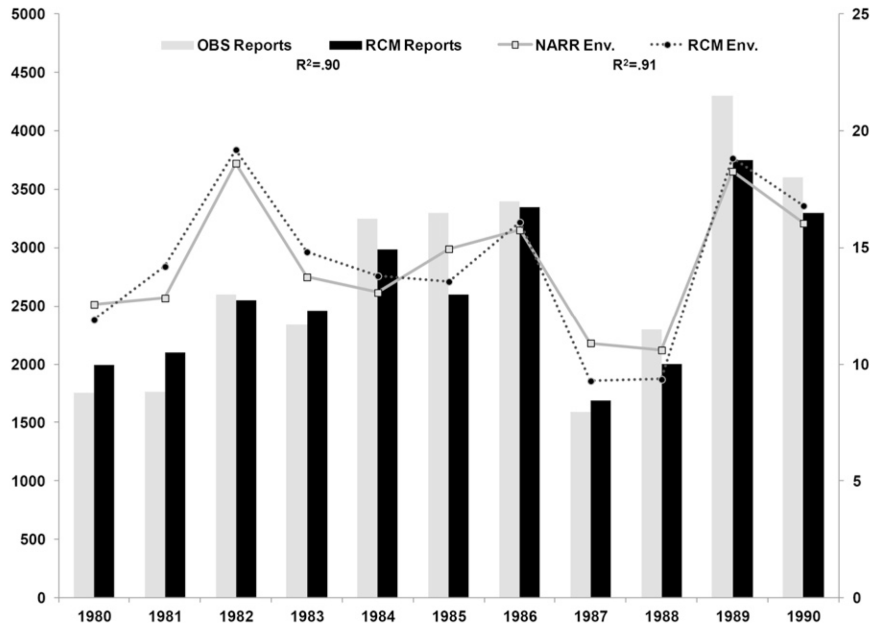

FIG. 3. Proxy RCM and observed HCW reports (bars; primary axis) and 0000 UTC domain-averaged proxy C-composite values (following Gensini and Ashley 2011) from the North American Regional Reanalysis and the RCM used in this study (lines; secondary axis).

shows a positive (negative) bias (Fig. 1). Additionally, RCM simulated and observed HCW exhibit similar interannual variability for the months March–May (Fig. 3; bars). For example, March–May 1987 and 1988 are notable in the U.S. HCW climatological record for their relatively low report occurrence. The RCM also depicts relative minimums in simulated HCW during these years. Although only 11 years are analyzed in this study, and therefore any advanced statistical analysis is inhibited, the historical period run of CCSM3 with the addition of a WRF as a RCM is able sufficiently capture observed variability of HCW at the 4-km, hourly scale during the months examined.

Spatial patterns of bias indicate population density likely plays a role in influencing observed reports relative to those simulated by the RCM (Fig. 4). For example, 1980–90 observed reports are shown to be higher near larger cities such as Dallas–Fort Worth, Oklahoma City, and Shreveport. Meanwhile, magnitudes of observed reports are lower than modeled values on the High Plains and in portions of Missouri and Arkansas where lack of population (and hence reports) is a key factor. In addition, there is a general underestimation of HCW occurrences by the RCM in many portions of the southeastern United States (Fig. 4). This underestimation regularly occurs in the month of May and may be attributable to convective mode and scale of forcing for ascent. For example, supercell thunderstorms are most common in the central plains of the United States, and a grid spacing of 4 km better resolves these mesocyclones versus the storm-scale rotation associated with quasi-linear convective severe weather common across the southeastern United States. Similar biases were found during the months of May and June by Trapp et al. (2011). Using these results, future period simulations can be bias-corrected to account for such errors (Christensen et al. 2008). However, it is unknown if these errors originate from the parent GCM, manifest in the RCM due to choice of model configuration, or are simply errors associated with reporting in *Storm Data*.

To supplement confidence in these simulated reports, environmental controls (i.e., CAPE and 0–6-km shear) known to support HCW were examined. These environmental controls serve as indicators to the climatological locations where one might expect HCW to occur. When restricting analysis of environments to 0000 UTC and resampling RCM output to a 32-km grid length [in order to compare to the North American Regional Reanalysis (NARR); Mesinger et al. 2006], it is shown that the RCM used herein also replicates the interannual variability of proxy significant severe weather environments (Fig. 3; lines). Line values (secondary axis) shown in Fig. 3 are RCM domain-averaged 0000 UTC frequencies of the proxy C composite parameter following the methodology of Gensini and Ashley (2011). While the statistical significance is limited in this relatively short temporal series, it is encouraging to see a historical period RCM run capture the interannual variability of

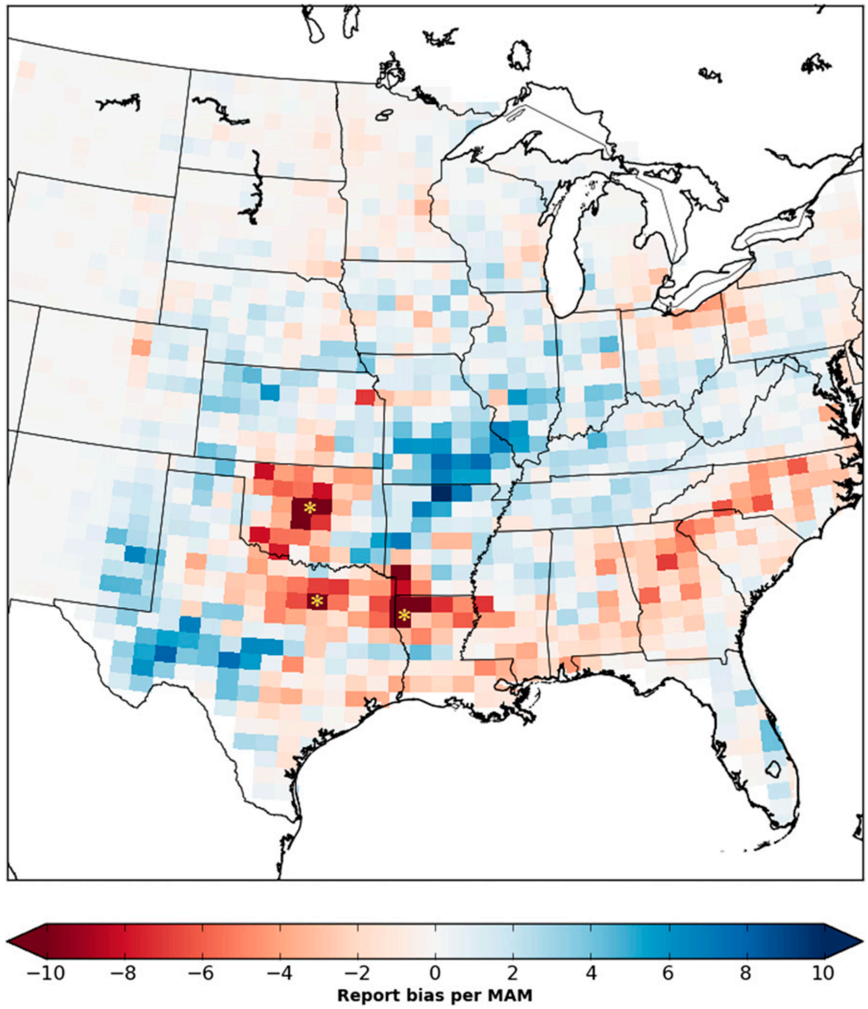

FIG. 4. Spatial difference between RCM proxy and observed severe weather reports for the period 1980–90. Yellow asterisks (*) indicate the locations of Oklahoma City, Oklahoma; Dallas–Fort Worth, Texas; and Shreveport, Louisiana.

environments favorable for HCW as depicted by the NARR. This strengthens the previous notion that RCMs can adequately capture the interannual variability of observed HCW.

In addition to seasonal spatiotemporal analysis, diurnal convective cycles were also examined (Fig. 5). This analysis suggests that high-resolution RCMs can adequately capture the diurnal cycle of HCW. Hourly modeled proxy reports explain 96% of the variability associated with observed reports. In fact, only one hour (0800 UTC) showed no overlap in the 10% error range of hourly observed and simulated HCW. The HCW peak in the RCM occurred at 0000 UTC (2890 reports), whereas observations peaked slightly earlier at 2300 UTC (3157 reports). This is similar to the WRF delayed maximum in rainfall intensity observed by Clark et al. (2007). It should be noted that agreement herein is likely improved due to stronger HCW forcing mechanisms (e.g., fronts) during the months March–May (Galway and Pearson 1981). It is probable that this similarity would diminish as the HCW season progresses into June–August when subtler forcing for ascent is present (Liu et al. 2006).

5. Summary and conclusions

We have utilized high-resolution (4 km; hourly) regional climate modeling to simulate a proxy for the variability of tornadoes, damaging thunderstorm wind gusts, and large hail across the eastern two-thirds of the United States for the months March–May during the period 1980–90. This process used GCM output from CCSM3 to drive WRF (the RCM). A proxy for HCW was developed utilizing methodology from Trapp et al. (2011)

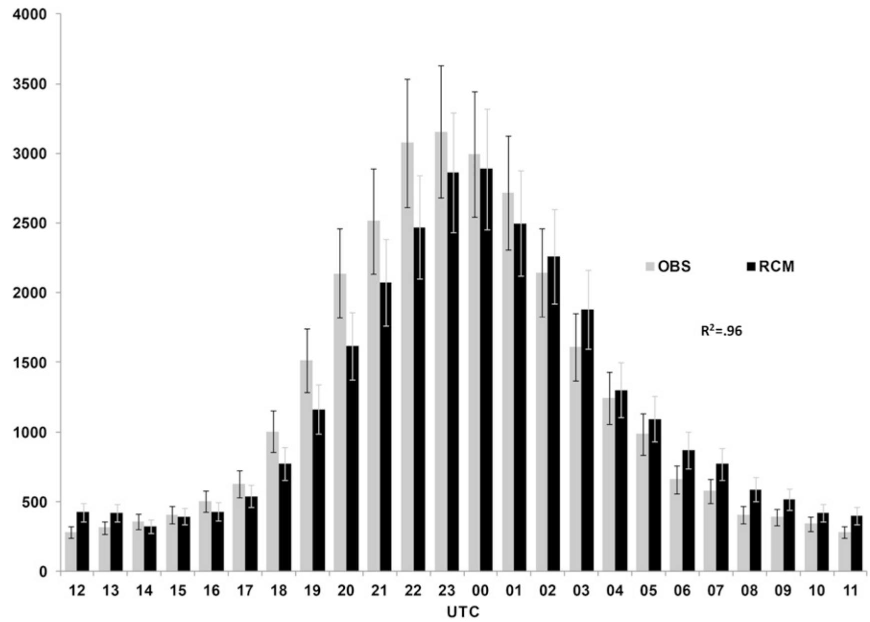

FIG. 5. Hourly diurnal frequency comparison of RCM simulated and observed severe weather reports. Error bars indicate the standard error.

and Robinson et al. (2013). However, continuous integration over the 3-month period was employed in this study to best replicate long-memory processes, a suggestion from previous research.

Overall, proxy HCW events simulated by the WRF as a RCM depict skill in the spatiotemporal distributions of hazardous thunderstorms during the months examined. Proxy report analysis is strengthened using an environmental control parameter that exhibits strong interannual correlation between RCM generated and reanalyzed environments. Spatial biases are present, indicating that evaluating HCW occurrence at small spatial scales should be done with caution. Instead, evaluations HCW occurrence from RCM output may be best done at GCM resolution. Along with studies such as Trapp et al. (2011) and Robinson et al. (2013), this research further indicates that dynamical downscaling of data with relatively coarse grid length to the resolution needed to explicitly resolve HCW is a productive endeavor.

To date, the main limitation of performing dynamical downscaling analysis for purposes of resolving HCW continues to be the lack of temporal length (i.e., we use an 11-yr period), owing to the computationally expensive nature of performing dynamical downscaling. This will be mitigated in the future as additional years and months are simulated, along with additional parent/child GCMs/RCMs, creating an ensemble estimation of both historical and future HCW occurrence. These GCM-driven dynamically downscaled scenarios must play a vital role in our understanding of potential changes in future HCW distributions and will serve as a comparison to environmental methods (Del Genio et al. 2007; Trapp et al. 2007a, 2009; Van Klooster and Roebber 2009; Gensini et al. 2013; Diffenbaugh et al. 2013) used to estimate such changes in previous research.

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