Climate change and hazardous convective weather in the United States: Insights from high-resolution dynamical downscaling

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By Kimberly Hoogewind

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Climate Change and Hazardous Convective Weather in the United States: Insights from High-resolution Dynamical Downscaling

For the degree of Doctor of Philosophy

Is approved by the final examining committee:

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Harold Brooks

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Approved by Major Professor(s): Michael Baldwin

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Head of the Departmental Graduate Program Date
CLIMATE CHANGE AND HAZARDOUS CONVECTIVE WEATHER IN THE UNITED STATES: INSIGHTS FROM HIGH-RESOLUTION DYNAMICAL DOWNSCALING

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Submitted to the Faculty of
Purdue University
by
Kimberly A. Hoogewind

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# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>LIST OF TABLES</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>LIST OF FIGURES</td>
<td>v</td>
</tr>
<tr>
<td>ABSTRACT</td>
<td>vi</td>
</tr>
<tr>
<td>CHAPTER 1. INTRODUCTION</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Motivation</td>
<td>1</td>
</tr>
<tr>
<td>1.2 Literature Review</td>
<td>2</td>
</tr>
<tr>
<td>1.2.1 Observations of Severe Storms</td>
<td>2</td>
</tr>
<tr>
<td>1.2.2 HCW Environments</td>
<td>6</td>
</tr>
<tr>
<td>1.2.3 Dynamical Downscaling</td>
<td>18</td>
</tr>
<tr>
<td>1.3 Research Objectives and Outline</td>
<td>22</td>
</tr>
<tr>
<td>CHAPTER 2. PROJECTED CHANGES IN HCW ENVIRONMENTS</td>
<td>24</td>
</tr>
<tr>
<td>2.1 Introduction</td>
<td>24</td>
</tr>
<tr>
<td>2.2 Data and Methods</td>
<td>24</td>
</tr>
<tr>
<td>2.2.1 Choice of GCM and Climate Change Scenarios</td>
<td>24</td>
</tr>
<tr>
<td>2.2.2 Defining a Potential HCW Day</td>
<td>26</td>
</tr>
<tr>
<td>2.3 Results</td>
<td>31</td>
</tr>
<tr>
<td>2.3.1 Mean Annual Changes in HCW Environments</td>
<td>31</td>
</tr>
<tr>
<td>2.3.2 Annual Cycle</td>
<td>44</td>
</tr>
<tr>
<td>2.4 Summary</td>
<td>61</td>
</tr>
<tr>
<td>CHAPTER 3. HIGH-RESOLUTION DYNAMICAL DOWNSCALING</td>
<td>63</td>
</tr>
<tr>
<td>3.1 Introduction</td>
<td>63</td>
</tr>
<tr>
<td>3.2 Data and Methods</td>
<td>63</td>
</tr>
<tr>
<td>3.2.1 Regional Climate Model</td>
<td>63</td>
</tr>
<tr>
<td>3.2.2 Estimating HCW Events from Model Output</td>
<td>68</td>
</tr>
<tr>
<td>3.3 Results</td>
<td>74</td>
</tr>
<tr>
<td>3.3.1 Brief Evaluation of the Downscaled Historical Simulations</td>
<td>74</td>
</tr>
<tr>
<td>3.3.2 HCW Activity</td>
<td>90</td>
</tr>
<tr>
<td>3.3.3 Insight into Hazard Type</td>
<td>110</td>
</tr>
<tr>
<td>3.4 Summary</td>
<td>131</td>
</tr>
<tr>
<td>CHAPTER 4. COMPARING MODELING APPROACHES</td>
<td>134</td>
</tr>
<tr>
<td>4.1 Introduction</td>
<td>134</td>
</tr>
<tr>
<td>4.2 Methods</td>
<td>134</td>
</tr>
<tr>
<td>4.3 Results</td>
<td>135</td>
</tr>
<tr>
<td>Section</td>
<td>Page</td>
</tr>
<tr>
<td>------------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>4.4 Summary</td>
<td>141</td>
</tr>
<tr>
<td>CHAPTER 5. SUMMARY AND CONCLUSIONS</td>
<td>143</td>
</tr>
<tr>
<td>REFERENCES</td>
<td>147</td>
</tr>
<tr>
<td>APPENDICES</td>
<td></td>
</tr>
<tr>
<td>APPENDIX A. SUPPLEMENTARY FIGURES FOR CHAPTER 2</td>
<td>159</td>
</tr>
<tr>
<td>APPENDIX B. SUPPLEMENTARY FIGURES FOR CHAPTER 3</td>
<td>162</td>
</tr>
<tr>
<td>APPENDIX C. SUPPLEMENTARY FIGURES FOR CHAPTER 4</td>
<td>172</td>
</tr>
<tr>
<td>APPENDIX D. DATA INFORMATION AND GRIB2 TABLE</td>
<td>178</td>
</tr>
<tr>
<td>VITA</td>
<td>183</td>
</tr>
</tbody>
</table>
LIST OF TABLES

Table                                                                                   Page
2.1 Proportion of HCW days delineated by the 0000Z relative to days defined over the
    1200–0600Z period for selected parameters.                                      29
2.2 Annual mean absolute change in parameter days for the RCP8.5 scenario
    for 2071–2100 as compared to 1971–2000.                                       40
2.3 Same as in 2.2 except for relative change (in %).                              40
2.4 Mean differences in days for several percentiles of the empirical CDFs
    shown in Figure 2.21.                                                          58
3.1 WRF configuration information.                                                   67
3.2 Seasonal mean error (ME) in °C for temperature (T) and dew point temperature
    (Td).                                                                          76
3.3 Pattern correlation for standardized anomalies of seasonal mean precipitation
    between WRF and PRISM.                                                         78
3.4 Mean error of 1971–2000 mean seasonal precipitation (inches) from down-
    scaled WRF simulation as compared to PRISM.                                    78
3.5 Pearson coefficient of linear correlation of mean standardized anomalies of
    precipitation between WRF and GFDL-CM3.                                         79
3.6 Pearson correlation coefficient values and root mean squared error (RMSE)
    between mean seasonal maxUH and UVV days as compared to observed
    severe weather days (1971–2000).                                               88
3.7 Pearson correlation coefficient values and root mean squared error (RMSE)
    for mean seasonal AFWAtor, AFWAhail, maxGRPL, and maxWIND days
    as compared to observed severe weather days by hazard type (1971–2000).    89
3.8 Change (in days) of the Gaussian smoothed peak probability of experiencing
    a maxUH and UVV day.                                                           105
3.9 Mean differences in days for several percentiles of the empirical CDFs for
    maxUH and UVV days and grid point frequencies.                                 108
3.10 As in Table 3.9, except for AFWAtor, AFWAhail, maxGRPL, and maxWIND,
    respectively.                                                                  130
4.1 Pearson correlation coefficients between the mean CONUS seasonal standardized anomalies of HCW days and days with maxUH $\geq 50 \ m^2 s^{-2}$ and days with UVV $\geq 20 \ ms^{-1}$ for both the historical and future periods.  

4.2 Slope, y-intercept, $R^2$, and ANCOVA p-values of the linear regression between environmental parameters and days with maxUH $\geq 50 \ m^2 s^{-2}$ and UVV $\geq 20 \ ms^{-1}$.

D.1 Grib2 Encoding Details
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Proportion of NDSEV accounted by 0000Z versus the 1200–0600Z time-frame for the 30-year historical (1971–2000) scenario.</td>
<td>29</td>
</tr>
<tr>
<td>2.2</td>
<td>Regional boundaries used for localized geographic analysis. The number of grid points (land only) for the entire CONUS and each region are listed.</td>
<td>30</td>
</tr>
<tr>
<td>2.3</td>
<td>Time series of annual regional mean anomaly, relative to 1971-2000 mean, of CONUS land points east of -105°W for (a) NDSEV, (b) NDSEV, (c) $NDSEV_{sig}$, (d) $NDSEV_{tor}$, (e) $STP$, and (f) $MLCAPE$ days. This historical period (1950-2005) is represented by the blue line, and RCP4.5 and RCP8.5 scenarios (2006-2100) are represented by the purple and red lines, respectively. A Gaussian filter is applied with $\sigma = 5$ years (darker blue, red, and purple lines), and bootstrapped 95% confidence intervals are shaded.)</td>
<td>32</td>
</tr>
<tr>
<td>2.4</td>
<td>Mean annual number of (a) $NDSEV_{1.6}$ days and the mean departure for future 30-year periods (2011–2040, 2041–2070, and 2071–2100)) for RCP4.5 (b),(e),(h), RCP8.5 (c),(f),(i), and the difference between the two future scenarios (RCP8.5 minus RCP4.5; (d),(g),(j)). Stippling represents where the distribution of yearly mean values are significantly different at the 95% confidence level.</td>
<td>34</td>
</tr>
<tr>
<td>2.5</td>
<td>As in 2.4, but for $NDSEV$ days.</td>
<td>35</td>
</tr>
<tr>
<td>2.6</td>
<td>As in 2.4, but for $NDSEV_{sig}$ days</td>
<td>36</td>
</tr>
<tr>
<td>2.7</td>
<td>As in 2.4, but for $NDSEV_{tor}$ days</td>
<td>37</td>
</tr>
<tr>
<td>2.8</td>
<td>As in 2.4, but for $STP$ days.</td>
<td>38</td>
</tr>
<tr>
<td>2.9</td>
<td>As in 2.4, but for days with $MLCAPE \geq 2000 \ JKg^{-1}$.</td>
<td>39</td>
</tr>
<tr>
<td>2.10</td>
<td>Box plots depicting the distribution of fractional proportion of CONUS land points east of -105°W land points for (a) NDSEV, (b) NDSEV, (c)$NDSEV_{sig}$, (d)$NDSEV_{tor}$, (e) $STP$, and (f) $MLCAPE$. Historical distributions are for the years 1971–2000 and RCP4.5, and RCP8.5 scenarios for 2071–2100.</td>
<td>42</td>
</tr>
<tr>
<td>Figure</td>
<td>Page</td>
<td></td>
</tr>
<tr>
<td>--------</td>
<td>------</td>
<td></td>
</tr>
<tr>
<td>2.11 Box plots depicting the distribution of daily maximum parameter values for days exceeding the minimum threshold for the Historical, RCP4.5, and RCP8.5 experiments. Historical distributions are for the years 1971–2000 and RCP4.5, and RCP8.5 scenarios for 2071–2100.</td>
<td>43</td>
<td></td>
</tr>
<tr>
<td>2.12 Changes in DJF mean annual days for RCP4.5 (a,c,e,g,i) and RCP8.5 (b,d,f,h,j) for $NDSEV_{1.6}$, $NDSEV$, $NDSEV_{sig}$, $NDSEV_{tor}$, $STP$, respectively. Stippling indicate where differences are statistically significant at the the 95% confidence level.</td>
<td>46</td>
<td></td>
</tr>
<tr>
<td>2.13 Same as Figure 2.3.2, except for MAM.</td>
<td>47</td>
<td></td>
</tr>
<tr>
<td>2.14 Same as Figure 2.3.2, except for JJA.</td>
<td>48</td>
<td></td>
</tr>
<tr>
<td>2.15 Same as Figure 2.3.2, except for SON.</td>
<td>51</td>
<td></td>
</tr>
<tr>
<td>2.16 Changes in RCP4.5 mean values of CAPE ($Jkg^{-1}$), $S06$ ($ms^{-1}$), and $CIN$ ($Jkg^{-1}$) for (a)–(c) DJF, (d)–(f) MAM, (g)–(i) JJA, and (j)–(l) SON compared to the historical period.</td>
<td>52</td>
<td></td>
</tr>
<tr>
<td>2.17 As in 2.16, except for RCP8.5.</td>
<td>53</td>
<td></td>
</tr>
<tr>
<td>2.18 Mean seasonal changes in the joint probability distribution of CAPE and $S06$ for the eastern CONUS (east of -105°W, land points only) for (a),(d) DJF, (b),(e) MAM, (c),(f) JJA, and (d),(h) SON compared to the historical period. RCP4.5 differences are depicted in (a)–(d) while RCP8.5 are depicted in (e)–(h). The solid, dashed, and dashed-dot black lines indicate where in the parameter space $NDSEV$, $NDSEV_{sig}$, and $NDSEV_{tor}$ thresholds are met. Stippling indicates where the differences are statistically significant.</td>
<td>55</td>
<td></td>
</tr>
<tr>
<td>2.19 Mean seasonal changes in the joint probability distribution of CAPE and $CIN$ for for the eastern CONUS (east of -105°W, land points only) for(a),(d) DJF, (b),(e) MAM, (c),(f) JJA, and (d),(h) SON compared to the historical period. RCP4.5 differences are depicted in (a)–(d) while RCP8.5 are depicted in (e)–(h).</td>
<td>56</td>
<td></td>
</tr>
<tr>
<td>2.20 30 year mean probability estimates of an environment day anywhere in the U.S. east of -105 °W (land points only) by Julian day for (a) $NDSEV_{1.6}$, (b) $NDSEV$, (c)$NDSEV_{sig}$, (d)$NDSEV_{tor}$, (e) $STP$, and (f) $MLCAPE$ days. The raw probabilities are represented by the scatter points, and a Gaussian filter is applied with $\sigma=15$ days, as in Brooks et al. (2003a), represented by the bold lines. The historical period (1971–2000) is represented by the navy blue line, and RCP4.5 and RCP8.5 scenarios (2071–2100) are represented by the purple and red lines, respectively.</td>
<td>59</td>
<td></td>
</tr>
</tbody>
</table>
2.21 Comparison of the mean empirical CDF of $NDSEV_{sig}$ days between the historical (solid line) and future (dashed line) periods for (a) RCP4.5 and (b) RCP8.5 scenarios. Bootstrapped 95% confidence intervals are shaded (blue: historical, red: future).

3.1 WRF domain for downscaled simulations.

3.2 Standardized anomalies of mean seasonal precipitation (1971-2000) for the downscaled WRF simulations (top) and the PRISM dataset (bottom) for (a) DJF, (b) MAM, (c) JJA, and (d) SON.

3.3 Comparison of standardized anomalies of mean seasonal precipitation (1971-2000) between the downscaled WRF simulations (top) and GFDL-CM3 (bottom) for (a) DJF, (b) MAM, (c) JJA, and (d) SON.

3.4 Mean number of days per season (top) and standardized anomalies (bottom) with daily precipitation accumulation exceeding (a) 0.25 mm, (b) 10 mm, (c) 25 mm, and (d) 50 mm.

3.5 Seasonal comparison of HCW days between the (a)–(d) SPC report database, (e)–(h) days with maxUH $\geq 50 \, m^2/s^2$, and (g)–(j) days with UVV $\geq 20 \, ms^{-1}$.

3.6 Comparison of seasonal mean severe hail days between the (a)–(d) SPC report database, (e)–(h) days with AFWAtor $\geq 30 \, ms^{-1}$.

3.7 Comparison of seasonal mean tornado days between the (a)–(d) SPC report database, (e)–(h) days with AFWAtor $\geq 30 \, ms^{-1}$.

3.8 Comparison of annual mean days with (a) observed severe convective wind gusts and (h) days with maxWIND $\geq 20 \, ms^{-1}$.

3.9 Smoothed distributions (based on histograms) for (a) maxUH, (b) UVV, and (c) REFC.

3.10 Mean annual number of days with REFC $\geq 50 \, dBZ$, maxUH $\geq 50 \, m^2/s^2$, and UVV $\geq 20 \, ms^{-1}$ for the (a)–(c) historical period (1971–2000) and (d)–(f) future period (2071–2100). The difference between the future and historical means are presented in (g)–(i), and stippling indicates where the distributions of annual means are statistically significant at the 95% confidence level.

3.11 Seasonal mean days with REFC $\geq 50 \, dBZ$ days for the (a)–(d) 1971–2000 period, (e)–(h) 2071–2100 period, and (i)–(l) the difference between the means of the two periods. From left to right, the columns represent seasons DJF through SON.
3.12 Seasonal mean normalized grid point frequency of \( \text{REFC} \geq 50 \ dBZ \) occurrences for the (a)–(d) 1971–2000 period, (e)–(h) 2071–2100 period, and (i)–(l) the difference between the means of the two periods. From left to right, the columns represent seasons DJF through SON. Stippling indicates where the distribution of seasonal means between the two periods are statistically significant at the 95% confidence level.

3.13 As in Figure 3.11, except for days with \( \text{maxUH} \geq 50 \ ms^{-2} \).

3.14 As in Figure 3.12, except for occurrences of \( \text{maxUH} \geq 50 \ ms^{-2} \).

3.15 As in Figure 3.11, except for days with \( \text{UVV} \geq 20 \ ms^{-1} \).

3.16 As in Figure 3.12, except for occurrences of \( \text{UVV} \geq 20 \ ms^{-1} \).

3.17 Mean diurnal distribution of \( \text{maxUH} \) (a)–(d) and \( \text{UVV} \) (e)–(h) by season for the historical (blue bars) and future (red bars) periods. Error bars indicate the 95% confidence interval estimated through a bootstrapping procedure.

3.18 30-year mean probability of experiencing (a) \( \text{maxUH} \geq 50 \ ms^{-2} \), (b) \( \text{UVV} \geq 20 \ ms^{-1} \), (c) \( \text{maxUH} \geq 100 \ ms^{-2} \), and (d) \( \text{UVV} \geq 30 \ ms^{-1} \) anywhere in the CONUS (east of -105°W, land points only) by Julian day. The raw probabilities are represented by the scatter points, and a Gaussian filter is applied with \( \sigma = 15 \) days, as in Brooks et al. (2003a), represented by the bold lines. The historical (1971–2000) and future (2071–2100) periods are represented by the navy and red lines, respectively.

3.19 Accumulated frequency of (a) \( \text{maxUH} \) days, (b) \( \text{maxUH} \) grid point frequency, and the empirical CDF of (c) \( \text{maxUH} \) days, (d) \( \text{maxUH} \) grid point frequency. Each individual year is plotted (historical in blue and future in red) with the means for the historical and future period represented by the solid and dashed black line, respectively.

3.20 As in 3.19, except for \( \text{UVV} \geq 20 \ ms^{-1} \).

3.21 Daily grid point frequency of (a) \( \text{maxUH} \geq 50 \ ms^{-2} \) and (b) \( \text{UVV} \geq 20 \ ms^{-1} \) for each year of the historical (blue lines) and future (red lines) periods. Raw data have been smoothed with a Gaussian filter (\( \sigma = 15 \) days) The mean daily frequency values for the historical (future) period are represented by the solid (dashed) black lines.

3.22 Smoothed distributions (based on histograms) depicting the distribution of values for (a) \( \text{AFWAtor} \), (b) \( \text{AFWAhail} \), (c) \( \text{maxGRPL} \), and (d) \( \text{maxWIND} \). The historical period is shown in blue and the future in red.
3.23 Mean annual number of days with (a) AFWAtor $\geq 30\ ms^{-1}$, (b) AFWAhail $\geq 25\ mm$, (c) maximum column integrated graupel $\geq 25\ kgm^{-2}$, and (d) hourly maximum 10 m wind speed $\geq 20\ ms^{-1}$ (in the presence of at least 40 dBZ reflectivity values at 1 km AGL).

3.24 As in Figure 3.11, except for occurrences of AFWAtor $\geq 30\ ms^{-1}$. 

3.25 As in Figure 3.11, except for occurrences of AFWAhail $\geq 25\ mm$. 

3.26 As in Figure 3.11, except for occurrences of maxGRPL $\geq 25\ kgm^{-2}$. 

3.27 As in Figure 3.11, except for occurrences of maxWIND $\geq 20\ ms^{-1}$. 

3.28 30-year mean probability of experiencing (a) AFWAtor $\geq 30\ ms^{-1}$, (b) $\geq 25\ mm$, (c) maxGRPL $\geq 25\ kgm^{-2}$, (d) maxWIND $\geq 20\ ms^{-1}$ anywhere in the CONUS (east of -105°W, land points only) by Julian day. The raw probabilities are represented by the scatter points, and a Gaussian filter is applied with $\sigma = 15$ days, as in Brooks et al. (2003a), represented by the bold lines. The historical (1971–2000) and future (2071–2100) periods are represented by the navy and red lines, respectively.

3.29 30-year mean probability of experiencing (a) AFWAtor $\geq 50\ ms^{-1}$, (b) $\geq 50\ mm$, (c) maxGRPL $\geq 50\ kgm^{-2}$, (d) maxWIND $\geq 30\ ms^{-1}$ anywhere in the CONUS (east of -105°W, land points only) by Julian day. The raw probabilities are represented by the scatter points, and a Gaussian filter is applied with $\sigma = 15$ days, as in Brooks et al. (2003a), represented by the bold lines. The historical (1971–2000) and future (2071–2100) periods are represented by the navy and red lines, respectively.

3.30 Empirical CDF of annual accumulated occurrence days for (a) AFWAtor $\geq 30\ ms^{-1}$, (b) $\geq 25\ mm$, (c) maxGRPL $\geq 25\ kgm^{-2}$, (d) maxWIND $\geq 20\ ms^{-1}$. Each individual year is plotted (historical in blue and future in red) with the means for the historical and future period represented by the solid and dashed black line, respectively.

3.31 Annual accumulated occurrence days for (a) AFWAtor $\geq 30\ ms^{-1}$, (b) $\geq 25\ mm$, (c) maxGRPL $\geq 25\ kgm^{-2}$, (d) maxWIND $\geq 20\ ms^{-1}$. Each individual year is plotted (historical in blue and future in red) with the means for the historical and future period represented by the solid and dashed black line, respectively.

3.32 Annual accumulated frequency of grid point occurrences for (a) AFWAtor $\geq 30\ ms^{-1}$, (b) $\geq 25\ mm$, (c) maxGRPL $\geq 25\ kgm^{-2}$, (d) maxWIND $\geq 20\ ms^{-1}$. Each individual year is plotted (historical in blue and future in red) with the means for the historical and future period represented by the solid and dashed black line, respectively.
3.33 Empirical CDF of annual accumulated frequency of grid point occurrences for (a) AFWAtor \(\geq 30 \text{ ms}^{-1}\), (b) \(\geq 25 \text{ mm}\), (c) maxGRPL \(\geq 25 \text{ kgm}^{-2}\), (d) maxWIND \(\geq 20 \text{ ms}^{-1}\). Each individual year is plotted (historical in blue and future in red) with the means for the historical and future period represented by the solid and dashed black line, respectively. 128

3.34 Daily grid point frequency of (a) AFWAtor \(\geq 30 \text{ ms}^{-1}\), (b) \(\geq 25 \text{ mm}\), (c) maxGRPL \(\geq 25 \text{ kgm}^{-2}\), (d) maxWIND \(\geq 20 \text{ ms}^{-1}\). Each year of the historical (blue lines) and future (red lines) periods. Raw data have been smoothed with a Gaussian filter \((\sigma=15 \text{ days})\). The mean daily frequency values for the historical (future) period are represented by the solid (dashed) black lines. 129

4.1 Standardized anomalies of (a),(c) \(NDSEV_{\text{sig}}\) days and (b),(d) days with maxUH \(\geq 50 \text{ m}^{2}\text{s}^{-2}\). The top row represents results from the historical simulations, and the bottom row the future projections. 136

4.2 Linear regression between U.S. (east of \(-105^\circ\text{W};\) land points only) monthly mean \(NDSEV_{\text{sig}}\) days and (a) days with maxUH \(\geq 50 \text{ m}^{2}\text{s}^{-2}\) and (b) UVV \(\geq 20 \text{ ms}^{-1}\) days. Monthly mean HCW environment days for each of the 30-years of historical (1971–2000; navy line and scatter points) and future (2071–2100; maroon line and scatter points) periods serve as the predictors. Bootstrapped 95% confidence intervals are shaded. 140

A.1 Mean seasonal changes in MLCAPE days (a)–(b) DJF, (c)–(d) MAM, (e)–(f) JJA, and (g)–(h) SON compared to the historical period. RCP4.5 differences are depicted in (a),(c),(e), and (g) while RCP8.5 are depicted in (b),(d),(f), and (h). 159

A.2 Mean seasonal changes in near-surface temperature (K) for (a)–(b) DJF, (c)–(d) MAM, (e)–(f) JJA, and (g)–(h) SON compared to the historical period. RCP4.5 differences are depicted in (a),(c),(e), and (g) while RCP8.5 are depicted in (b),(d),(f), and (h). 160

A.3 As in Figure A.2 except for near-surface specific humidity \((\text{gkg}^{-1})\). 161

B.1 Mean MAM and JJA seasonal changes in days with maxUH \(\geq (a),(b) 75\), (c),(d) 100, and (e),(f) 150 \text{m}^{2}\text{s}^{-2}.\) 162

B.2 Mean MAM and JJA seasonal changes in days with UVV \(\geq (a),(b) 30\), (c),(d) 35, and (e),(f) 40 \text{m}^{-1}.\) 163

B.3 Mean MAM and JJA seasonal changes in days with REFC \(\geq 60 \text{ dBZ}.\) 164
Figure B.4 30-year mean probability of experiencing maxUH $\geq 50$ within the (a) Midwest, (b) Northeast, (c) Southeast, (d) Southern Plains, (e) Northern Plains, and (f) West regions according to Julian date. The raw probabilities are represented by the scatter points, and a Gaussian filter is applied with $\sigma=15$ days, as in Brooks et al. (2003a), represented by the bold lines. The historical (1971–2000) and future (2071–2100) periods are represented by the navy and red lines, respectively.

Figure B.5 As in Figure B.4, except for UVV $\geq 20$ $ms^{-1}$.

Figure B.6 Daily grid point frequency of maxUH $\geq 50$ $m^2s^{-2}$ for the (a) Midwest, (b) Northeast, (c) Southeast, (d) Southern Plains, (e) Northern Plains, and (f) West regions. Raw sums have been smoothed with a Gaussian filter ($\sigma=15$ days) The mean daily frequency values for the historical (future) period are represented by the solid (dashed) black lines.

Figure B.7 As in Figure B.6, except for UVV $\geq 20$ $ms^{-1}$.

Figure B.8 Mean annual number of days with (a) AFWAtor $\geq 50$ $ms^{-1}$, (b) AFWAhail $\geq 50$ mm, (c) maximum column integrated graupel $\geq 50$ kgm$^{-2}$, and (d) hourly maximum 10 m wind speed $\geq 30$ $ms^{-1}$ (in the presence of at least 40 dBZ reflectivity at 1 km AGL).

Figure B.9 Mean DJF, MAM and JJA seasonal changes in days with AFWAtor $\geq$ (a),(c),(e) 40 and (b),(d),(f) 50 $ms^{-1}$.

Figure B.10 Mean MAM and JJA seasonal changes in days with maxGRPL $\geq$ (a),(b) 35, (c),(d) 50 kgm$^{-2}$.

Figure B.11 Mean MAM and JJA seasonal changes in days with AFWAhail $\geq$ (a),(b) 35, and (c),(d) 50 mm.

Figure C.1 Linear regression between U.S. (east of -105$^\circ$W; land points only) monthly mean (a) $NDSEV_{1,6}$, (b) $NDSEV$, (c) $NDSEV_{tor}$, and (d) STP days with monthly mean days with maxUH $\geq 50$ $m^2s^{-2}$. Monthly mean HCW environment days for each of the 30-years of historical (1971–2000; navy line and scatter points) and future (2071–2100; maroon line and scatter points) periods serve as the predictors. Bootstrapped 95% confidence intervals are shaded.

Figure C.2 As in Figure C.1, except for days with UVV $\geq 20$ $ms^{-1}$. 

C.3 Linear regression between regional mean $NDSEV_{sig}$ and maxUH ($\geq 50 m^2s^{-2}$) days for the (a) Midwest, (b) Northeast, (c) Southeast, (d) southern Plains, (e) northern Plains, and (f) West regions. Monthly mean HCW environment days for each of the 30-years of historical (1971–2000; navy line and scatter points) and future (2071–2100; maroon line and scatter points) periods serve as the predictors. Bootstrapped 95% confidence intervals are shaded for each line.

C.4 As in Figure C.3, except for days with UVV $\geq 20 ms^{-1}$.

C.5 Linear regression between U.S. (east of -105°W; land points only) monthly mean $NDSEV_{sig}$ with monthly mean days with maxUH $\geq 50 m^2s^{-2}$ for (a) DJF, (b) MAM, (c) JJA, and (d) SON. Monthly mean HCW environment days per season for each of the 30-years of historical (1971–2000; navy line and scatter points) and future (2071–2100; maroon line and scatter points) periods serve as the predictors. Bootstrapped 95% confidence intervals are shaded.

C.6 As in Figure C.3, except for days with UVV $\geq 20 ms^{-1}$. 
ABSTRACT

Hoogewind, Kimberly A. PhD, Purdue University, May 2016. Climate Change and Hazardous Convective Weather in the United States: Insights from High-resolution Dynamical Downscaling. Major Professors: Michael E. Baldwin and Robert J. Trapp.

Global climate model (GCM) projections increasingly suggest that large-scale environmental conditions favorable for hazardous convective weather (HCW) may increase in frequency in the future due to anthropogenic climate change. However, this storm environment-based approach is undoubtedly limited by the assumption that convective-scale phenomena will be realized within these environments. The spatial resolution of GCMs remains much too coarse to adequately represent the scales at which severe convective storms occur, including processes that may lead to storm initiation. With the advancement of computing resources, however, it has now become feasible to explicitly represent deep convective storms within a high-resolution regional climate model.

This research utilized the Weather Research and Forecasting (WRF) model to produce high-resolution, dynamically downscaled simulations for the continental United States under historical (1971–2000) and future (2071–2100) climate periods using GCM data provided by the Geophysical Fluid Dynamic Laboratory Climate Model version 3 (GFDL-CM3). Model proxies were used to provide an objective estimate of the occurrence of simulated severe weather and how their spatiotemporal distribution may change in the future under an aggressive climate change scenario. Results demonstrated that severe storms may increase in both their frequency and intensity in the future. In comparison to the projected changes in HCW favorable environments from the GCM, the dynamically downscaled largely agree in terms of the seasonal timing and spatial patterns of greatest potential change in activity by the end of the
21st century. Likewise, each approach supports the notion that severe weather activity may begin earlier within the annual cycle and also later within the calendar year, such that the severe weather season is lengthened. However, by all indications, the environment-event frequency relationship has been altered in future climate, such that the uptick in the number of days with simulated HCW events does not increase proportionally to the rise in days with HCW favorable environments. Such an outcome supports the motivation for continued use of dynamical downscaling to overcome the limitations of the GCM-based environmental analysis.
CHAPTER 1. INTRODUCTION

1.1 Motivation

Hazardous convective weather (HCW) collectively describes severe convective storms which produce large hail, damaging surface winds, and tornadoes. Annually, HCW poses a significant threat to life and property, and remains a prominent source of weather related losses in the United States. For example, severe storms and tornadoes accounted for over one-third of the 151 weather-related disasters exceeding $1 billion in damages during the time period 1980–2013 (NCDC, 2014). Billion dollar weather events resulting from severe local storms have undergone the largest increase compared to other weather events (Smith and Katz, 2013), and severe convective storms often result in more injuries and fatalities than other significant extreme weather phenomena, such as hurricanes (Diffenbaugh et al., 2008). While economic losses due to severe convective hazards have been on an upward trend (e.g., Brooks and Doswell, 2001; Smith and Katz, 2013), it is important to emphasize that the increase may be more attributable to socioeconomic factors that to an enhanced frequency of severe weather events (e.g., Changnon, 2003, 2009; Bouwer, 2011). For example, population increases heighten vulnerability to weather disasters by virtue of enhanced exposure as population grows and expands into previously unpopulated areas (e.g., Hall and Ashley, 2008; Ashley et al., 2014; Strader and Ashley, 2015). Nonetheless, it has been postulated that a warming global climate may increase severe weather in the future. Should such an increase be realized, future losses due to HCW may be expected to increase, and even more so when non-meteorological factors that impact human vulnerability are considered (Gensini et al., 2014a).

Recent efforts to address how HCW may change in the future have mainly focused upon the favorable environmental conditions for the development of severe thun-
understorms and their potential changes as depicted by global climate model (GCM) projections. Results largely agree that favorable convective environments are likely to increase through the 21st century (Trapp et al., 2007a, 2009; Van Klooster and Roebber, 2009; Diffenbaugh et al., 2013; Seeley and Romps, 2015). However, there remain major sources of uncertainty that arise from the inability of GCMs to resolve the scales at which severe storms occur, including sources of convective initiation, due to their coarse grid spacing. High-resolution, dynamically downscaled simulations of future climate to assess HCW has been advocated in order to address the aforementioned uncertainties in a more explicit manner. While a growing area of research, relatively few studies have utilized this approach to investigate convective storms under future climate scenarios, primarily due to the computational expense. However, with the advancement of computing resources, this approach has become more feasible. To better understand this question, this project seeks to produce dynamically downscaled, high-resolution simulations of historical and future climate for the purpose of assessing potential impacts upon the frequency, spatial distribution, intensity, and seasonality of HCW due to climate change.

1.2 Literature Review

1.2.1 Observations of Severe Storms

Thunderstorms which produce convective wind gusts $\geq 50$ knots, hail $\geq 0.75''$ (upgraded to 1.0'' in 2010), and/or a tornado are classified as a severe event (Bluestein, 2013); their significant severe counterparts represent the upper echelon of intensity, with $\geq 65$ knots, 2+ inch hail, and/or a tornado greater than F/EF-2 intensity. While relatively rare occurrences, HCW may have large societal impacts. In order to assess possible future changes in the distribution, knowledge of the historical climatological record of such severe events is a vital. Studying the observational record of severe convective weather is an intuitive first approach to assess trends in HCW, however, it is not without challenges. A major limitation arises due to the lack of an accu-
rate, long-term record of severe storms and tornadoes. While the United States has a relatively robust database of severe weather reports compared to other countries, accounting for trends within the data is complex. Data collection is difficult to compile and is strongly susceptible to reporting inadequacies (Brooks et al., 2003b; Doswell et al., 2005; Brooks, 2013). Inflation of the number of reports since the database began in the 1950s has been significant; the number of tornadoes reported annually has increased two-fold (with nearly all of the increase coming from F/EF-0 tornado reports), and the number of non-tornadic severe weather reports has increased by more than an order of magnitude (e.g., Brooks and Dotzek, 2008). This trend is strongly influenced by many non-meteorological factors such as population growth and density, increased public awareness, and reporting procedures (e.g., Brooks et al., 2003b; Doswell et al., 2005; Brooks and Dotzek, 2008). Further, there are other significant issues known to plague the U.S. tornado database, such as statistically significant changes in the distribution of reported path length over the years in addition to likely overrating of tornadoes within the early period of record due to retrospective rating (Brooks et al., 2003b; Verbout et al., 2006).

Using a more conservative approach that examined tornado days (the occurrence of at least one tornado) rather than raw report frequencies, Brooks et al. (2003b) was able to evaluate the mean geospatial distribution of tornadoes for the 1980–1999 period. The annual threat of tornadoes occurrence illustrates a “C” shape in relatively higher tornado probability broadly ranging from southwestern Gulf coast states up through the central Plains and turning eastward into the Ohio River Valley. Significant tornadoes are shown to be more prevalent in the Southern Plains over Oklahoma with an axis of enhanced probability extending north into the central Plains and another axis extending eastward from Oklahoma into Dixie Alley. Other studies in tornado climatology have generally highlighted these same areas (e.g., Dixon et al., 2011; Coleman and Dixon, 2014; Farney and Dixon, 2014) as having the greatest annual threat. As far as the annual cycle, all tornadoes, significant or otherwise, tend to follow a very similar spatial pattern throughout the year, with the largest risk
confined to the southern Gulf coast states early in the year then spreads further north and west during the spring months with the maxima occurring in the southern Plains. During the summer months, the favored tornado regions shift northward into the northern Plains, and by fall migrates back toward the south.

The same approach was used by Doswell et al. (2005) to analyze the climatology for severe hail and convective wind events. The annual threat for severe hail ≥ 0.75” is vast, encompassing much of the United States east of the continental divide, with the largest threat areas concentrated in the Central and Southern Plains states. In terms of the annual mean number of days with severe wind (≥50 knots), much of the CONUS east of the Rocky Mountains are at risk for such events, with the greatest threat occurring east of the Mississippi during the warm season. Both significant hail and wind events are generally confined to the Plains states but with some evidence of an axis of greater probabilities extending from the northern Plains eastward into the Ohio Valley.

Several studies have related the climatology of HCW to the storm morphology, or mode, which produced the event. This is an important consideration, particularly for forecasting, as hazard type can vary according to storm mode. From such studies, it has become evident that supercellular storm modes are the most prominent producers of severe weather, and in particular, significant severe hail and tornadoes (e.g., Gallus et al., 2008; Duda and Gallus, 2010; Grams et al., 2012; Smith et al., 2012). In fact, strong (F/EF-3+) tornadoes and significant severe hail events are nearly exclusively associated with supercell storms (Smith et al., 2012). The relationship between HCW and convective mode has been shown to have strong regional and seasonal signatures. For example, tornadoes produced by quasi-linear convective systems (QLCSs) are more common in the spring have a higher relative frequency across Mississippi and Ohio River Valleys, a displacement further to the east when compared to other modes (Trapp et al., 2005; Smith et al., 2012). More evenly distributed among mode, however, are significant severe wind events, which Smith et al. (2012) suggests presents the greatest forecasting challenge among hazards.
Investigation into climatological characteristics evident within the report database have been undertaken. Recent studies have shown that while the annual number of tornado (F/EF-1+) days have remained relatively constant while the interannual variability has actually increased (Brooks et al., 2014; Elsner et al., 2014; Tippett, 2014). In essence, this points toward the idea that fewer annual tornado days are being observed, however, there have been more tornadoes on those days. Brooks et al. (2014) suggest the change is likely not an artifact of the known database problems, and that it may be suggestive of changing large-scale environmental ingredients. Indeed, Tippett (2014) found that the tornado environment index (TEI), a composite index which incorporates monthly averaged convective precipitation and storm relative helicity, has also demonstrated an increase in the year-to-year variability, thus supporting a physical linkage between tornado reports and the environmental conditions. The results of Elsner et al. (2014) lend further support that found that a fewer number of tornado days may be occurring on an annual bases, but an increase in the number of tornadoes on “big” tornado days. While these trends could possibly be, at least in part, attributed to the observational record, there may be some evidence that a change in the climate could actually have occurred. Additionally, Brooks et al. (2014) also suggests that an earlier start to the season may be occurring, though it is much more variable within the last 15 years. Along similar lines, Long and Stoy (2014) found that the peak tornado activity in the central U.S. has shifted about 7 days earlier over the past 60 years. As a result, changes in tornado climatology and seasonality may be occurring, potentially due to a changing climate.

Due to the challenges associated with the observational record of severe storm reports, determining longer-term changes of severe thunderstorm and tornado activity from historical records is difficult to gauge. Consequently, the Fifth Assessment Report (AR5) from the Intergovernmental Panel on Climate Change (IPCC) has concluded that there is low confidence in observed trends in small-scale weather phenomena such as hail and thunderstorms (Hartmann et al., 2013). It has been advocated that large-scale environmental conditions known to be associated with severe weather
may be used as a proxy for their occurrence, as their observations may be more reliable. Thus the spatial distribution and temporal trends of favorable environmental conditions then be studied (e.g., Griffiths et al., 1993; Brooks et al., 2003a).

1.2.2 HCW Environments

Historical HCW Environments

Characterizing the environmental “ingredients” associated with severe convective storms is a well-established practice (e.g., Doswell et al., 1996). Doswell et al. (1996) discussed three main ingredients needed for the formation of deep, moist convection: moisture, instability, and a lifting mechanism. Sufficient moisture in the low levels is needed such that a parcel of air has a level of free convection (LFC), which describes the point in which an air parcel will become positively buoyant compared to its environment, and will rise without being forced. Buoyancy (B) is a measure that quantifies both the moisture and instability ingredients, and given sufficient moisture such that a parcel has an LFC, convective available potential energy (CAPE; Moncrieff and Miller, 1976) is simply the vertically integrated buoyancy (B) between the level of free convection (LFC) and the equilibrium level (EL):

\[ \text{CAPE} = \int_{z_{LFC}}^{z_{EL}} B \]

where B is defined as

\[ B = g \frac{T_v - \overline{T_v}}{\overline{T_v}}. \]

\( T_v \) represents the virtual temperature of an air parcel, while \( \overline{T_v} \) is the virtual temperature of the environment, and g the gravitational acceleration. CAPE is an oft used parameter to describe the instability of the atmosphere, or in other words, the potential energy of the environment that may be converted to kinetic energy as a parcel of air rises above the LFC to the EL. CAPE values >0 Jkg\(^{-1}\) could be consid-
ered a necessary, though insufficient condition for the formation of deep convection (Trapp, 2013). Lastly, the typical large scale ascent is much too weak to adequately lift the parcel to its LCL and LFC and subsequently initiate convection. Therefore, a focused mechanism on the mesoscale is needed. Such triggering phenomena may include orographic lifting, boundaries such as fronts, drylines, or convective outflow, and sea-breeze fronts to name a few (Brooks et al., 2007). An additional ingredient, strong vertical wind shear, is necessary for organized convection. Stronger vertical wind shear, given sufficient instability, aids in promoting increased organization and longevity of severe storms (e.g., Markowski and Richardson, 2011).

Observational studies have employed the use of proximity soundings to characterize the environment of severe convective storms since the mid-21st century (e.g., Fawbush and Miller, 1954; Beebe, 1955, 1958). However, the use of observed radiosonde observations can be problematic as they are sparsely distributed and limited in time, and thus may not truly be representative of environmental conditions present during and prior to severe weather occurrences. More recently, model or reanalysis derived soundings (“pseudo-soundings”) have been used for proximity studies which provide for an enhanced spatial and temporal resolution (e.g., Thompson et al., 2003, 2007; Brooks et al., 2003b). Information extracted from the soundings may be used to develop reliable relationships between environmental conditions and severe storms. Both observational and modeling studies have shown that the organization and severity of storms have a strong dependence upon their environment, in particular measures of instability (CAPE) and vertical wind shear (e.g., Weisman and Klemp, 1982, 1984; Rasmussen and Blanchard, 1998; Evans and Doswell, 2001; Craven and Brooks, 2004).

Given the lack of consistent observations of events, large-scale environmental observations may serve as a proxy for severe weather, and the spatial distribution and temporal trends can be studied. In line with this approach, Brooks et al. (2003b) compared reports of significant severe weather from 1997-1999 with derived pseudo-soundings from the National Center for Environmental Prediction-National Center
for Atmospheric Research (NCEP-NCAR) global reanalysis dataset (Kalnay et al., 1996). A statistical discriminant relationship using CAPE and 0-6 km deep layer shear (S06; magnitude of the vector wind difference between the 6 km and the near surface winds) was developed and subsequently used to distinguish between significant severe thunderstorm (hail $\geq$ 2 inches, wind $\geq$ 65 knots, and/or tornado $\geq$ F/EF2+) and marginally severe environments. The resultant equation for the discriminant line based on the analysis was found to be

$$CAPE \times S06 \geq 46,800$$

(1.3)

As shown, this relationship weights the vertical wind shear slightly more than CAPE. Subsequently, this discriminant relationship was applied to the reanalysis dataset to estimate the global distribution of environments conducive for significant severe storms, represented in terms of number of days, conducive to significant severe thunderstorms and tornadoes. Notable regions of enhanced severe weather frequency are found downstream of mountain ranges and poleward of a warm water body. By and large, the U.S. east of the Rocky Mountains is the most favorable region in the world for severe weather, in particular tornadoes. Allen et al. (2011) performed a similar analysis for Australia and found a discriminant line that paralleled that of Brooks et al. (2003b).

Additional studies have been able to examine the large-scale environmental conditions conducive to severe weather from reanalysis datasets (Brooks et al., 2007; Brooks, 2009; Gensini and Ashley, 2011) and GCMs (Marsh et al., 2007) to assess the frequency and distribution of severe environments within historical climate. Many studies have used a slightly modified, though similar approach to Brooks et al. (2003b). Generally, it has become to use the strict product of CAPE and S06 (equivalent to the significant severe parameter of Craven and Brooks (2004)), defined as

$$CAPE \times S06 \geq X \ m^3 s^{-3}$$

(1.4)
where X represents some minimum threshold (Marsh et al., 2007, 2009; Trapp et al., 2007b, 2009; Gensini et al., 2014a; Diffenbaugh et al., 2013) to determine an environment as potentially severe. The threshold value of 10,000 $m^3s^{-3}$ has been used as a lower boundary for a general severe convective environment, while larger thresholds of 20,000 $m^3s^{-3}$ and 30,000 $m^3s^{-3}$ may indicate significant severe hail/wind and significant tornado environments, respectively. Gensini and Ashley (2011) used a similar approach, but also required that CIN exceed -75 $Jkg^{-1}$ when examining convective environments from the North American Regional Reanalysis (NARR; Mesinger et al., 2006). Similarly, Robinson et al. (2013) analyzed trends in environments from the NCEP-NCAR reanalysis dataset using (1.4). Overall, long term trends from reanalyses have shown that there appears to be little, if any, trend for an increasing number of environments supportive of severe convection despite the large increase in reports (Gensini and Ashley, 2011; Robinson et al., 2013), though Sander et al. (2013) did find some correlation between the increasing number of significant economic losses from thunderstorm events and severe environments. Nonetheless, (Trapp et al., 2009) suggest that any statistically significant change as a result of anthropogenic climate change may not emerge for decades.

**Future HCW Environments**

Human activities have significantly increased concentrations of greenhouse gases (GHGs), including carbon dioxide ($CO_2$), methane ($CH_4$), nitrous oxide ($N_2O$), and other well-mixed greenhouse gases such as halocarbons, from preindustrial levels (Myhre et al., 2013), and such increases have likely attributed to over half of the observed warming over the period 1951–2010 (Bindoff et al., 2013). Most of the aforementioned GHGs remain within the atmosphere for long periods of time, up to 200 years (Hartmann, 1994, p. 320). As a consequence of elevated levels of GHGs and other anthropogenic forcing (e.g., aerosols), increased warming at the surface due to an intensified atmospheric greenhouse effect is anticipated due to changes in ra-
diative forcing. Warming suggests a corresponding increase in low-level moisture due to the strong dependence of water vapor upon temperature as demonstrated by the Clausius-Clapeyron equation; it is commonly noted that a 7% increase in saturation vapor pressure will be realized for every 1°C of warming in the lower troposphere (e.g., Held and Soden, 2006). An increase in moisture may in turn lead to increased extreme precipitation events for which observational evidence substantiates (Groisman et al., 2005; Min et al., 2011; Kunkel et al., 2013). While this is also suggestive of a potential increase in convection, it is insufficient to infer that extreme precipitation events may arise due to an increase in HCW (Trapp, 2013). Nonetheless, let us consider some potential theoretical implications of climate change upon HCW.

The increasing temperature and moisture within the lower troposphere may both play a role in contributing to an increase in CAPE, particularly where increases in both occur in tandem. Larger warming in the lower troposphere relative to air aloft could allow for steeper mid-level lapse rates (and consequently greater CAPE). Through parcel theory, it can be shown that the theoretical maximum updraft speed \(w_{\text{max}}\) is related to CAPE as follows (e.g., Markowski and Richardson, 2011, p.43):

\[
w_{\text{max}} = \sqrt{2 \times \text{CAPE}}
\]  

Hence, as CAPE increases in accordance with both temperature and near-surface specific humidity increases, it becomes indicative that storms in the future may have stronger updrafts. Subsequently, stronger updrafts may be supportive of producing more intense precipitation and greater hail production and growth, though updraft strength itself is not a sufficient indication of hail formation (Johns and Doswell, 1992). Increased precipitation rates could lead to an enhancement of precipitation drag and consequently stronger downdrafts; resultant convective outflow may potentially lead to stronger surface winds and thus a greater threat for severe convective wind events (e.g., Trapp et al., 2007a). Uncertainty, however, plagues the notion of an increased frequency and size of hail due to the opposing effects of stronger updrafts and the consequent rise in the melting level height due to tropospheric warming (e.g.,
Xie et al., 2008, 2010; Mahoney et al., 2012; Dessens et al., 2015). As a result, a larger layer of warmer temperatures would enhance melting of hail as it falls toward the surface, thereby reducing the size and/or amount of hail at surface. However, Xie et al. (2010) demonstrated with a 1-D hail model that only smaller hail sizes would be impacted when the melting level height is increased, while there would be little, if any, impact upon larger hailstones. Both observations and GCM projections depict greater warming at high northern latitudes than in the tropics, also known as Arctic amplification. As a consequence, a reduction in the equator to pole temperature gradient is anticipated. Through the thermal wind relationship, a corresponding reduction in the vertical wind shear should accompany a weakened meridional temperature gradient. As vertical wind shear is imperative to storm organization, it is unclear whether the competing effects of increased mean CAPE and decreased mean vertical wind shear would results in a greater number of storms that are sub-severe or whether the CAPE will dominate the shear and increase severe weather occurrence. High vertical wind shear environments, given sufficient instability, are more preferential to tornadoes and severe hail formation, and severe wind events may be more likely in environments of lower deep-layer shear (e.g., Brooks, 2013). Thus, the potential effect could be a decreased occurrence of tornadoes and large hail but an increased number of severe convective wind occurrences in the future.

An important consideration also involves the potential impact of Arctic amplification upon extratropical cyclones (ETCs) and large-scale wave patterns. While severe weather is not exclusively associated with ETCs, convection is often noticeably associated with their occurrence. ETCs act to precondition the environment by contributing to low-level moistening and destabilization via differential advection, and additionally are associated with synoptic scale forcing for ascent. Additionally, frontal boundaries associated with ETCs often are a source of convective initiation. Uncertainty remains as to how ETCs may be affected under future climate scenarios due to Arctic amplification and the resulting impact on the static stability and meridional baroclinicity in which drive ETCs. Further, it is not well understood whether
the competing effects of a reduced equator to pole temperature gradient in the lower
troposphere due to Arctic amplification and the strengthened upper level temperature
gradient due to tropical amplification will increase or decrease ETC activity in gen-
eral, nor is it certain whether storm tracks will be impacted (Christensen et al., 2013).
Climate model projections from CMIP5, however, suggest there may be a reduced
global frequency of ETCs overall with the potential for a poleward shift in ETC tracks,
though this latter trend is more confident for Southern Hemisphere ETCs (Collins
et al., 2013). Over the continental United States, however, Chang (2013) found a
strong consensus among a 23 member ensemble of CMIP5 models that points toward
a reduction in ETC frequency across all seasons, with the strongest decrease occurring
during the summer and the smallest decrease in the spring. Moreover, while closely
tied to ETCs, some work has been done to examine the climatology of atmospheric
fronts in present and future terms of atmospheric fronts. (Catto et al., 2014) applied
an objective front identification technique based upon the thermal front parameter
(TFP; see Hoogewind (2012) for a thorough review on objective frontal identification
techniques) to 18 models from The Coupled Model Intercomparison Project Phase 5
(CMIP5; Taylor et al., 2012) under the historical and the aggressive RCP8.5 scenarios.
Frontal frequency in the northern hemisphere was found to decrease; in particular,
higher latitudes saw a greater decrease in frequency and intensity, consistent with the
reduction in the meridional temperature gradient.

It has also been suggested that high latitude warming may result in the amplifica-
tion and slower progression of Rossby waves, leading to an increased risk for extreme
weather (Francis and Vavrus, 2012, 2015). Barnes (2013) and Barnes et al. (2014),
however, have shown that these results may be dependent upon methodology and that
changes in blocking patterns in the Northern Hemisphere are not currently supported
by reanalysis datasets.

Under anthropogenically enhanced greenhouse forcing, it remains uncertain as to
how severe thunderstorms may respond. In general, changes in the mean values of
necessary parameters, namely an increase in CAPE and decrease in deep layer shear,
lend conflicting insight. More of interest is the combination of these parameters and how they change concurrently and on individual days (e.g., Brooks, 2006). This theoretical exercise is further complicated by the uncertainty of how other large-scale features in the atmosphere will be impacted in a warming world, such as the potential change in frequency and storm tracks of ETCs and the large scale wave pattern. In particular, these weather features often play a significant role in convective initiation; thus, the question of if and how convective initiation might change in the future has largely been unanswered.

Some progress has been made toward addressing these theoretical uncertainties in large-scale environmental conditions conducive to severe weather from GCM projections of future climate. However, to gain insight as to the impact of climate change on future severe storm environments it is imperative to investigate whether or not GCM models can reasonably depict the historical distribution of environments. In most instances, GCMs have been found to at least qualitatively capture the distribution of favorable severe weather environments and their annual evolution (e.g., Marsh et al., 2007, 2009; Trapp et al., 2007a, 2009; Lee, 2012; Gensini et al., 2014a; Diffenbaugh et al., 2013). This is encouraging and lends further validation to the approach.

Some insight into the general question of future climate change on convective storminess has shown that indeed a warming world may lead to more frequent storms. In particular, as the presence of lightning may be used to infer the presence of deep convection (e.g., Mansell et al., 2007), previous studies have examined how lightning frequency may change. Price and Rind (1994) developed a formulation to estimated intracloud and cloud-to-ground lightning frequency using variables from a GCM’s convective parameterization scheme. Under a doubling $CO_2$ experiment, it was found that lightning frequency could increase by as much as 30%, with the largest changes occurring in the northern hemisphere summertime (JJA). On average, it was found that for every 1°C of warming corresponds to $\sim$5-6% increase in lightning frequency. More recently, Romps et al. (2014) developed a simple proxy—the product of CAPE and precipitation rate—for lightning occurrence that explains 77% of the variance of
lightning flashes in the CONUS. Applied to an ensemble of 11 GCMs, projections over
the 21st century suggest that lightning strikes in the CONUS may increase by 50% by
the end of the 21st century. In the same vein, (Del Genio et al., 2007) examined
updraft speed as a more direct measure of storm intensity. While changes in mean
updraft speed in a future climate under a CO\textsubscript{2} doubling experiment were found to
be small, stronger updrafts were found to occur more often. In combination with
weakened shear, it was concluded that the distribution of severe occurrences may not
change dramatically in the future, but rather the most severe storms may occur more
often.

Results from implicit modeling approaches examining future climate projections
have shown that the frequency of environments supportive of severe convective weather
may increase through the mid and late 21st century for areas in the U.S. east of the
Continental Divide (Trapp et al., 2007a,b, 2009; Van Klooster and Roebber, 2009;
Gensini et al., 2014a; Diffenbaugh et al., 2013; Seeley and Romps, 2015). Nearly all
of the studies show that CAPE values increase among most climate model projections,
largely attributed to increased low level moisture, and the mean vertical wind shear
decreases in the future. This result is consistent with the aforementioned theoretical
considerations.

Using the product of CAPE and S\textsubscript{06} (1.4), Trapp et al. (2007a) examined the
number of days in which a severe environment (NDSEV) occurred within a regional
climate model and three GCMs over the period 1948–2099. While the overall trend
for increasing CAPE and decreasing shear was evident, and increase in NDSEV was
noted, it was suggested then that the increases in CAPE may overcome the decreases
in shear. As a result, the overall environments supportive of severe weather may
increase throughout the 21st century. Using a modified approach, Trapp et al. (2009)
slightly modified the approach of Trapp et al. (2007a) such that NDSEV may only
occur given that \( \text{CAPE} \geq 100 \, Jkg^{-1}, \vec{V}_{6km} \geq \vec{V}_{sfc} \geq 5 \, ms^{-1}, \) \text{ and } |S\textsubscript{06}| \geq 5 \, ms^{-1}.
Additionally, a new NDSEV parameter that additionally required the occurrence
of convective precipitation was introduced in an attempt to account for convective
initiation. Moreover, this study also examined ETC frequency, and it was found that NDSEV increases in the future despite an overall decrease in annual ETC frequency evident within a 5 member ensemble of GCMs. The decrease in ETCs was more pronounced in the cool season (November–January), though, when the threat for severe convection is climatologically less prevalent.

Gensini et al. (2014a), using regional climate model from the North American Regional Climate Change Assessment Program (NARCCAP; Mearns et al., 2012), found regional increases in significant severe environments. Using a multi-model ensemble of Canadian Regional Climate Model (CRCM) experiments over the period 1960–2099, Paquin et al. (2014) examined how convective environments and convective precipitation occurrences may change in a warming climate. Using both formulations of (1.3) and (1.4), it was found that each illustrated a statistically significant increase of about 50% over the 140-year period. Trends in convective precipitation (≥25 mm day\(^{-1}\)) also underwent statistically significant increase of 25–30% over the period; additionally, convective precipitation was also found to become slightly more intense. Regionally, the areas of the central and northern Great Plains into the Canadian Prairies in addition to the Gulf Coast states were found to have the strongest increases.

Examining data from the most recent state-of-the-art GCMs from the CMIP5 experiment, Diffenbaugh et al. (2013) found that the 10 member ensemble demonstrated a robust increase in the number of days with favorable severe environments over the eastern United States. The ensemble agreement was most robust in the springtime while model solutions diverged during the summer months, particularly in the central Plains. This is likely due to some model projections depicting more widespread aridification in these areas (Seeley and Romps, 2015). Furthermore, their analyses highlighted that while mean S06 does decrease in the projections, the number of days with low S06 was concentrated on days with low CAPE values. Likewise, an identifiable shift of high CAPE days occurring in the presence of lower CIN was evident across the model suite. It was also suggested that the number of days sup-
portive of tornadoes may increase in the future due to the rising number of days with high low-level (0–1 km) vertical wind shear (S01) and large CAPE. Overall, increases in NDSEV were evident across all models and emerged before the end of the 21st century.

Unlike Diffenbaugh et al. (2013), Seeley and Romps (2015) demonstrated results of future convective scenarios from both RCP4.5 and RCP8.5 experiments using a subset of high-performing GCMs. Those defined as high-performing demonstrated greater ability to capture past and present climatological conditions, a method motivated by the divergence of climate model solutions during the summer months illustrated by Diffenbaugh et al. (2013). Strong increases on the order of 50–180% were evident by the end of the 21st century (2079–2088) during the spring months among this small ensemble. Summertime increases were also evident among 3 out of the 4 models, with the outlier solution predicting drier conditions in the Great Plains states. Moreover, they also examined the sensitivity between using equations (1.3) versus (1.4) and found only slight deviations in the magnitude of projection, but both displayed the same overall trend.

While many GCMs predict an overall increase in CAPE and decreased vertical wind shear, other approaches have been used to address the issue. The study conducted by Van Klooster and Roebber (2009) used an artificial neural network to assess the relative potential for convective initiation under future climate scenarios. Although CAPE and S06 were used, as in other studies, the addition of surface convergence was added in attempt to account for an initiation mechanism. The potential for severe convection was found to increase in the future, with CAPE the primary contributor leading to the increase. Using a different methodology, Lee (2012) performed a principal component analysis using synoptic scale variables (geopotential height at 500 and 700 hPa, and 850 hPa temperature) and related them to those conditions found in tornadic environments. Each of these studies suggest a greater frequency of severe storms may occur in the future, and interestingly, results from both Lee (2012) and Van Klooster and Roebber (2009) suggest the possibility of a
lengthening HCW season, with perhaps a trend toward increased occurrence in the earlier months of the year.

Collectively, most studies conclude that an increase in severe thunderstorms may occur in the future over the CONUS, due to the increasing number of days with favorable environmental conditions capable of producing severe thunderstorms. Similar approaches have been used to examine how environments may change elsewhere in the world (Marsh et al., 2009; Allen and Karoly, 2014; Allen et al., 2014). Although there is growing evidence of an increased trend of favorable environments capable of producing severe thunderstorms, at the time of the latest assessment report was released, the IPCC considered the number of studies too few to preclude any estimation of future likelihood of severe local storms (Collins et al., 2013). Additionally, the implicit modeling approach of studying the favorable large-scale environmental conditions is undoubtedly limited by the assumption that the convective-scale phenomena will be realized within these environments. The resolution of GCMs remain much too coarse to adequately represent the scales at which severe weather phenomena occur, including processes that may lead to the initiation of convective clouds. Additionally, the most common method of identifying potentially severe environments through the product of CAPE and shear may fail to capture events that occur in low CAPE, high shear regimes under strong synoptic forcing, as is common during the cool season in the southeastern U.S. (e.g., Brooks et al., 2007; Gensini et al., 2014a; Sherburn and Parker, 2014). As a result, dynamical downscaling approaches (i.e., using coarser GCM data as the initial and boundary conditions for higher resolution, limited-area models) using high-resolution convection allowing models have been suggested as an alternative approach (Trapp et al., 2007a,b; Brooks, 2009, 2013; Diffenbaugh et al., 2013; Gensini et al., 2014a).
1.2.3 Dynamical Downscaling

Downscaling techniques, both statistical and dynamical, attempt to bridge the resolution mismatch between the coarse resolution of GCMs (or reanalyses) and finer scales wherein information is desired for climate change impact assessment (e.g., Wilby and Wigley, 1997; Fowler et al., 2007). Dynamical downscaling refers to the use of a higher resolution limited area model (LAM), which derives its initial and boundary conditions from the driving GCM or reanalysis, to obtain higher resolution detail. In this way, sub-grid scale features may be better resolved (e.g., topography, coastlines, land cover), though results will still likely be strongly influenced by the large-scale forcing from the driving parent model. This technique has long been used in numerical weather prediction, but was only utilized as a regional climate modeling approach beginning in the late 1980s (e.g., Dickinson et al., 1989). Compared to statistical downscaling, which utilizes an empirically derived statistical relationship between scales, dynamical downscaling is much more computationally expensive, and thus the number of simulations that can be completed are typically reduced and usually confined to shorter time periods, or “time slices,” to make them more affordable (Fowler et al., 2007; Xue et al., 2014). Nonetheless, with a greater demand for future climate change projections at more localized scales, high-resolution regional climate modeling is becoming increasingly popular.

Many aspects of the experimental design need to be considered carefully when designing dynamical downscaling experiments. In particular, the domain size, location, and resolution of the area to be simulated. It has been shown that results can be sensitive to the domain size, and larger domains tend to allow for better development of finer scales, particularly when spectral nudging is used such that the regional climate model (RCM) remains consistent in the large fields with the driving GCM (Leduc and Laprise, 2009). Placement of domain boundaries should not, in general, be placed over areas of complex topography (Rummukainen, 2010). As the main goal of dynamical downscaling is to add finer scale detail while retaining the
larger scale details of the GCM, the integration procedure chosen can have profound impacts upon the simulation. Continuous integration can often result in “climate drift” within the RCM such that the overall climate deviates significantly from the driving GCM. Spectral or interior nudging along with more frequent initializations of the atmosphere have been advocated to combat this problem (von Storch et al., 2000; Pan et al., 1999; Lo et al., 2008; Hong and Kanamitsu, 2014). In this way, the larger scale fields are either being nudged toward or reset to those represented by the GCM. For a more in-depth overview of some of these issues, and others such as nesting and resolution jump, the reader is referred to Rummukainen (2010), Xue et al. (2014), and Hong and Kanamitsu (2014).

With the advancement of computing resources in addition to the growing availability of GCM data on a sub-daily temporal frequency, it has now become feasible to produce very high-resolution simulations through dynamical downscaling of climate model projections. While still computationally expensive, utilizing a high-resolution non-hydrostatic mesoscale model to allow for an explicit treatment of deep convection technique would allow for the model to intrinsically develop the relationship between the large scale environment and the ensuing convective events, and thus account for convective initiation. Explicit convection refers to one that does not employ a cumulus parameterization. In general, a horizontal grid spacing of 4-km or less has been deemed sufficient to resolve the larger convective circulations without the need for parameterization (Weisman et al., 1997), though the appropriateness of using a cumulus parameterization is still somewhat uncertain at a grid spacing between 4- and 10-km (e.g., Molinari and Dudek, 1992; Deng and Stauffer, 2006). Some argue that a horizontal grid spacing on the order of 100 m or less may be needed to fully resolve convection (Bryan et al., 2003) and thus a cumulus parameterization may still be needed (Deng and Stauffer, 2006). Nonetheless, studies have been shown that convection-allowing numerical forecasts have greater forecast skill, particularly in terms of convection, than forecasts which use a cumulus parameterization (e.g.,
Strongly motivated by the inherent uncertainties present in the U.S. database of severe storm reports, previous work has demonstrated the concept of dynamical downscaling using global reanalysis data to construct “synthetic” regional climatologies of severe storms (Trapp et al., 2011; Robinson et al., 2013). Trapp et al. (2011) used a sequence of daily reinitialized, 24-hour forecasts using the Weather Research and Forecasting (WRF) model. The model was run at a convection permitting 4.25-km horizontal grid spacing for the months of April, May, and June, when severe convective weather is most frequent, using the NCEP-NCAR reanalysis as initial and boundary conditions. A model proxy was used to estimate the occurrence of a simulated severe weather occurrence (hail, wind, and/or tornado) based on the coupling of updraft helicity (UH) in the 2-5 km AGL layer, a measure of storm rotation, and the simulated radar reflectivity (Z) exceeded 40 m²s⁻² and 50 dBZ, respectively. The model proxy demonstrated some degree of skill in emulating the climatological distribution of severe convective storms. Robinson et al. (2013) conducted a similar study for the 20 year period 1990–2009, but used an artificial neural network to estimate severe occurrences, finding that UH and CAPE were the most important factors in determining a model simulated storm to be severe. Simulated reports and environmental controls over the period exhibited little to no trend, despite the known inflation of reports in the database, which overall agrees with the findings of Gensini and Ashley (2011).

More recently, Gensini et al. (2014a) produced a high-resolution (4-km) dynamically downscaled climatology using WRF and driving data from a historical global climate simulation for the months of March–May for the period 1980–1990 using the Community Climate System Model version 3 (CCSM3). As in Trapp et al. (2011), the UH-Z proxy was used to estimate all severe hazards; downscaled simulations were found to reasonably capture the interannual variability and diurnal cycle of observed severe reports. However, just as in Trapp et al. (2011), an underestimation of severe
occurrences was noted in May which may be attributed to the inability of the model proxy to account for convective mode or the scale of forcing for ascent. Overall, each of these studies have shown that the climatological distribution of severe convection can reasonably be replicated using coarse initial and boundary conditions, either furnished by a reanalysis or GCM dataset, to drive high-resolution convection allowing models.

In regards to future climate, a growing number of studies have produced high-resolution dynamically downscaled simulations from GCM data to assess changes in climate, such as precipitation (e.g., Kendon et al., 2012; Mahoney et al., 2013; Lauer et al., 2013; Harding et al., 2013; Prein et al., 2013; Rasmussen et al., 2011, 2014). Prein et al. (2015) provides an extensive overview of the use of convection-allowing models for the purpose of regional climate modeling. Yet, few studies have used such an approach to assess changes in HCW. Mahoney et al. (2012) produced high-resolution WRF simulations (1.33-km) over Colorado and examined how hailstorm frequency and intensity may change in the future. By examining the graupel/hail term within the microphysics scheme, it was found that for warm-season extreme precipitation events, hail reaching the surface was significantly decreased owing to the increased height of the melting level. Further, Gensini and Mote (2015) produced high-resolution (4-km) continuously integrated seasonal simulations for the months of March, April, and May during a future period (2080–2090) climate using a CCSM3. Results indicate that compare to the historical baseline, a statistically significant increase in severe weather activity is noted in March with an overall increased tendency for severe with the March-May months. Additionally, variability of severe weather was also shown to increase in the future with the potential for increased mean occurrences. This study appears to be the first of its nature to examine the impact of increasing greenhouse forcing upon future severe thunderstorms occurrences within the United States via dynamical downscaling with a convection-allowing model.
1.3 Research Objectives and Outline

Overall, very few studies have performed high-resolution convection allowing simulations for the purpose of investigating the impacts upon HCW under future climate change scenarios. In fact, no study has used the most current GCM data from CMIP5 to estimate HCW occurrences. Additionally, previous work has not attempted to simulate the complete annual cycle of HCW, and has been limited to shorter time-slices (e.g., 11-years Gensini et al., 2014a; Gensini and Mote, 2015). The lack of longer-term studies in this arena is strongly influenced by the expensive computational nature of high-resolution regional climate modeling. To better address these gaps in the literature, this work seeks to produce dynamically downscaled, high-resolution simulations for the entire annual cycle and for a longer time period (30-years) for both historical and future climate. The Geophysical Fluid Dynamics Laboratory (GFDL) Climate Model version 3 (CM3) will serve as the parent model due to its ability to adequately capture the historical climatology of convective ingredients and environments (Diffenbaugh et al., 2013; Seeley and Romps, 2015). Analysis of the simulations will seek to assess the potential impacts upon the frequency, spatial distribution, intensity, and seasonality of overall HCW activity due to anthropogenic climate change.

The organization of this dissertation is as follows. Chapter 2 will examine the changes in several convective parameters as projected by GFDL-CM3 for two different climate change scenarios. Of question here is the difference in representation of favorable environments given different trajectories of potential climate change, both in magnitude and location, and the point at which the solutions begin to diverge. Next, Chapter 3 will describe the methodology for producing the high-resolution regional climate simulations. Subsequently, findings from the analysis of storm-scale proxies used to estimate the occurrence of HCW and potential changes due to anthropogenic greenhouse forcing will be presented. Further, exploratory analysis into potential changes upon specific hazard types (tornado, wind, hail) will also be performed. A comparison between the environmental changes and the modulation of
climate suggested by the RCM will ensue in Chapter 4. Finally, the manuscript will conclude with a summary and discussion of the overall findings of this work.
CHAPTER 2. PROJECTED CHANGES IN HCW ENVIRONMENTS

2.1 Introduction

This chapter will investigate the large-scale changes depicted by GFDL-CM3 GCM for a historical period and two future climate change projection scenarios. In this way, potential changes that may occur can be examined before the dynamical downscaling process, and additionally, insight into the differences between future climate scenarios can be assessed. It is also of importance to understand the behavior of the driving model prior to using it as a means for dynamical downscaling. Analysis in a subsequent chapter will compare the two different approaches (environmental analysis vs. dynamical downscaling) to examine the climate change and HCW connection.

2.2 Data and Methods

2.2.1 Choice of GCM and Climate Change Scenarios

The Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012) is the latest suite of atmosphere-ocean coupled global climate model (AOGCM; hereafter simply referred to as GCM) and earth system model (ESM) experiments to aid in the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (Collins et al., 2013, AR5). Over 20 modeling groups have contributed to this effort with over 50 different models being used for simulation experiments, many of which include several ensemble members (Taylor et al., 2012). As a result, over 3 petabytes of data are available. As a part of the core model simulations, CMIP5 model experiments include an historical run, initialized in 1850 and run through 2005, which incorporate observed changes in atmospheric composition (greenhouse gases, aerosols, and volcanic influences), solar output, and time-evolving land cover
Future projections were conducted using four separate representational concentration pathways (RCPs) that embody a range of future projections of radiative forcing realized through diverse contributions from population growth, socioeconomic and emission scenarios, technological developments, and land use (e.g., Moss et al., 2010; Van Vuuren et al., 2011; Taylor et al., 2012). The RCPs, denoted as RCP2.6, RCP4.5, RCP6, and RCP8.5, lead to radiative forcing levels (i.e. the difference between incoming and outgoing radiation at the top of the atmosphere due to changes in atmospheric composition) of 2.6, 4.5, 6, and 8.5 $W m^{-2}$ by 2100. RCP2.6 represents a “peak and decay” scenario, where radiative forcing reaches a maximum of 3 $W m^{-2}$ by mid-century and decays toward 2100; it is meant to represent a scenario where mitigation leads to lowered GHG concentrations. The two mid-range stabilization scenarios are represented by RCP4.5 and RCP6. Lastly, RCP8.5 is the most aggressive scenario, leading to radiative forcing of 8.5 $W m^{-2}$ by the year 2100. This equates to a quadrupling of $CO_2$ concentration (>1370 ppm) from preindustrial levels (Moss et al., 2010; Van Vuuren et al., 2011).

Both Diffenbaugh et al. (2013) and Seeley and Romps (2015) have demonstrated that GFDL-CM3 is a high-performing GCM in terms of historical climate. When compared to both reanalysis and radiosonde observations of convective parameters such as CAPE, CIN, and NDSEV, it was found to reasonably recreate the observed climatology of those variables, both spatially and in magnitude. GFDL-CM3 consists of atmosphere, ocean, land surface, and sea-ice components. The atmospheric model component (AM3) utilizes a finite-volume dynamical core, a $2.5^\circ \times 2^\circ$ longitude-latitude ($\sim$200 km) horizontal grid spacing, and contains 48 vertical levels with a model top of 1 hPa. A hybrid sigma-pressure vertical coordinate system is used, and the vertical resolution varies from approximately 70 m in the lowest portions of the atmosphere and increasing to 1-1.5 km in the upper troposphere to 3-4 km in the stratosphere (Donner et al., 2011). For a complete description of the physical parameterizations used within GFDL-CM3 simulations, the reader is referred to Donner et al. (2011). The ocean model component of CM3 uses the Modular Ocean Model
version 4pl (MOM4pl; Griffies et al., 2011). The horizontal grid spacing for MOM4pl is finer than that of the atmospheric component of CM3, at 1° × 1° latitude and longitude, and a tripolar horizontal grid is utilized. The model consists of 50 vertical levels using a rescaled height coordinate system which is analogous to the eta vertical coordinate system used in atmospheric modeling (Griffies et al., 2011).

Herein, results will be shown for the historical experiment and the RCP4.5 and RCP8.5 climate change scenarios for the 21st century. The choice to examine two future scenarios will identify at what point the two scenarios begin to diverge in terms of their representation of the frequency of favorable convective environments. To this end, results will begin to quantify how severe weather environments may change given the forcing differences between a mid-range mitigation scenario and an aggressive scenario with no reduction in GHG emissions. Results will depict mean changes throughout the 21st century with particular emphasis placed upon the last 30 years (2071–2100).

2.2.2 Defining a Potential HCW Day

As in previous studies, the number of generic severe thunderstorm environment days based upon Eq. (1.3) (referred to as $N_{SEV_{1.6}}$) and Eq. (1.4). For the latter, three different thresholds will be examined. As suggested by Craven and Brooks (2004), thresholds of 10,000, 20,000, and 30,000 $m^3s^{-3}$ were utilized to represent potentially severe, significant severe, and significant tornado environments, hereafter defined as $N_{SEV}$, $N_{SEV_{sig}}$, and $N_{SEV_{tor}}$, respectively. To this end, both the frequency and intensity may be examined. For each of these quantities, it was required that \(\text{CAPE} \geq 100 \text{ Jkg}^{-1}\), \(\text{S06} \geq 5 \text{ ms}^{-1}\), and \(\text{CIN} \geq -100 \text{ Jkg}^{-1}\) must also be met. The latter was introduced in order to reduce the frequency of environments that are strongly capped and unlikely to produce convection, similar to the approach taken by Gensini and Ashley (2011). In the formulation of the aforementioned quantities, CAPE is computed using a parcel representing the mixed layer within the lowest 100
hPa of the atmosphere, and S06 is computed as the magnitude of the vector difference between winds at 6 km and the surface.

Additionally, other severe weather composite indices will be investigated. Previous studies have tended to focus on the simple aspect of daily frequency of general severe thunderstorm environments, with little investigation into the potential changes in environments conducive for tornadoes. It has been shown that stronger shear and storm relative helicity (SRH) in the lowest 1 km and higher low-level relative humidity (and thus lower LCL heights) to be important for the development of significant tornadoes (Rasmussen and Blanchard, 1998; Rasmussen, 2003; Thompson et al., 2003; Grams et al., 2012; Thompson et al., 2012), and Diffenbaugh et al. (2013) did demonstrate that the number of days with large CAPE and low-level wind shear increased among an ensemble of CMIP5 models. Thompson et al. (2003) introduced the significant tornado parameter (STP) which combines CAPE, S06, 0–1 km SRH, and LCL heights. STP has been shown to have skill in discriminated between significant and non-significant tornadic environments when STP exceeds a value of 1. A slightly modified version of the significant tornado parameter (STP) as the version defined in Thompson et al. (2003) will be used, following Gensini and Marinaro (2015). STP is defined here as

\[
STP = \left( \frac{SBCAPE}{1500 \text{ Jkg}^{-1}} \right) \times \left( \frac{S06}{20 \text{ ms}^{-1}} \right) \times \left( \frac{SRH1}{150 \text{ ms}^{-1}} \right) \times \left( \frac{2000 - SBLCL}{1000 \text{ m}} \right)
\]

(2.1)

where SBCAPE and SBLCL refer to surface based CAPE and lifted condensation level, respectively. Term 2 is set to a value of 1.5 if S06 > 30 ms\(^{-1}\) and 0 where S06<12.5 ms\(^{-1}\), and Term 4 is set to 1 if SBLCL < 1000 m or 0 if >2000. While a CIN term is not explicitly included, STP is set to zero if \( \geq -100 \text{ Jkg}^{-1} \). In calculating SRH, the storm motion is estimated as 75% of the magnitude and 30° to the right of the mean wind in the lowest 10 km. Finally, while not a severe environment per se, days with large CAPE values (MLCAPE \( \geq 2000 \text{ Jkg}^{-1} \)) will be investigated as in
Brooks et al. (2003a) and Trapp et al. (2009). All of these variables were interpolated to a 1° latitude-longitude grid in order to facilitate a more consistent comparison with previous work (i.e. Diffenbaugh et al., 2013; Seeley and Romps, 2015).

Within the literature, it has become most common to examine convective environments in terms of the number of days which meet the set criteria. In this regard, most studies utilize the 0000Z time to estimate the daily occurrence of a favorable environment. In this work, however, an HCW day is defined at a point such that if the minimum parameter threshold is exceeded at any time over a 24-hr period between 1200Z and 1200Z. In this way, the time period corresponds with the valid time over which the Storm Prediction Center (SPC) convective outlooks are valid and verified.

The motivation for this departure of method is to account for potentially severe environments that occur outside of the diurnal peak time, such as cool season events which have a weaker diurnal dependence (e.g., Gensini and Ashley, 2011). For example, Figure 2.1 demonstrates the mean proportion of days identified by the 0000Z time versus the 24-hour period defined by 1200, 1800, 0000, and 0600Z for the historical period 1971–2000. While indeed a large majority of NDSEV days can be accounted for by the 0000Z time (CONUS average of ~68%), especially within the central U.S., the proportion decreases further east and west. Loosely based upon those defined by Trapp et al. (2009) and Robinson et al. (2013), six different regions are defined in Figure 2.2. The average proportions of days for different parameters for the CONUS and all regions are listed in Table 2.1 for different parameters. As can be seen, for most regions and parameters, favorable environments at 0000Z account for over half of the total defined over a 24-hour period (over 79% in the northern and southern Great Plains). However, the fact that as much as 40–50% of the total days could be missed for some of the regions (and for STP) reinforces the chosen methodology.
Figure 2.1. Proportion of NDSEV accounted by 0000Z versus the 1200–0600Z timeframe for the 30-year historical (1971–2000) scenario.

Table 2.1
Proportion of HCW days delineated by the 0000Z relative to days defined over the 1200–0600Z period for selected parameters.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>CONUS</th>
<th>Midwest</th>
<th>Northeast</th>
<th>Southeast</th>
<th>West</th>
<th>S. Plains</th>
<th>N. Plains</th>
</tr>
</thead>
<tbody>
<tr>
<td>STP</td>
<td>0.541</td>
<td>0.556</td>
<td>0.523</td>
<td>0.462</td>
<td>0.672</td>
<td>0.519</td>
<td>0.572</td>
</tr>
<tr>
<td>NDSEV</td>
<td>0.676</td>
<td>0.662</td>
<td>0.534</td>
<td>0.683</td>
<td>0.561</td>
<td>0.793</td>
<td>0.801</td>
</tr>
<tr>
<td>NDSEV_{1.6}</td>
<td>0.670</td>
<td>0.654</td>
<td>0.531</td>
<td>0.682</td>
<td>0.552</td>
<td>0.793</td>
<td>0.792</td>
</tr>
<tr>
<td>NDSEV_{sig}</td>
<td>0.711</td>
<td>0.640</td>
<td>0.604</td>
<td>0.605</td>
<td>0.805</td>
<td>0.797</td>
<td>0.813</td>
</tr>
<tr>
<td>NDSEV_{tor}</td>
<td>0.778</td>
<td>0.717</td>
<td>0.864</td>
<td>0.679</td>
<td>0.983</td>
<td>0.831</td>
<td>0.846</td>
</tr>
<tr>
<td>MLCAPE</td>
<td>0.820</td>
<td>0.775</td>
<td>0.850</td>
<td>0.810</td>
<td>1.000</td>
<td>0.855</td>
<td>0.837</td>
</tr>
</tbody>
</table>
Figure 2.2. Regional boundaries used for localized geographic analysis. The number of grid points (land only) for the entire CONUS and each region are listed.
2.3 Results

2.3.1 Mean Annual Changes in HCW Environments

As a first means of investigating the temporal trends of the historical and future RCP4.5 and RCP8.5 pathways, the mean annual number days are computed for the eastern CONUS (land points east of -105°W) for each parameter from 1950–2100. Anomalies are computed relative to the 1971–2000 baseline as a means to quantify the projected increases and expressed as a percentage of change. These anomalies for $NDSEV_{1.6}$, $NDSEV$, $NDSEV_{sig}$, $NDSEV_{tor}$, $STP$, and $MLCAPE$ days are presented in Figures 2.3(a)–2.3(f), respectively. All environment days show strong increases over the 21st century for both the mid- and high-range scenarios, with the strongest relative increases in annual environment frequency produced by RCP8.5 after the middle of the century, when the two pathways begin to diverge in their projections. By 2100, mean regional increases of $NDSEV$ by nearly 100% (50–60%) are depicted by RCP8.5 (RCP4.5), with mean anomalies of 60% (30%) for $NDSEV_{sig}$. The largest relative anomalies are evident in the number of $MLCAPE$ days and for the higher thresholds for the CAPE-S06 product, with the former increasing from a regional average of 5–7 days per year to nearly 25 days per year by 2100 in the RCP8.5 scenario. Increases of 90–150% in the annual number of $STP$ days are by the future scenarios. Each of the parameters show that RCP4.5 and RCP8.5 projections start to diverge between the mean annual anomalies emerging after 2050–2060 with much larger interannual variability relative to the historical period mean. This suggests may be indicative that the increasing variability of HCW favorable environmental conditions found within the observational record (e.g., Tippett, 2014) may continue and increase throughout the 21st century.

The climatology of annual $NDSEV_{1.6}$, $NDSEV$, $NDSEV_{sig}$, $NDSEV_{tor}$, $STP$, and $MLCAPE$ environment days over the historical period (1971–2000) are illustrated in Figures 2.5(a), 2.4(a), 2.6(a), 2.7(a), 2.8(a), and 2.9(a), respectively. It is very apparent that the central U.S. is the most climatologically favored area for
Figure 2.3. Time series of annual regional mean anomaly, relative to 1971-2000 mean, of CONUS land points east of -105°W for (a) $NDSEV$, (b) $NDSEV_{1.6}$, (c) $NDSEV_{sig}$, (d) $NDSEV_{tor}$, (e) $STP$, and (f) $MLCAPE$ days. This historical period (1950-2005) is represented by the blue line, and RCP4.5 and RCP8.5 scenarios (2006-2100) are represented by the purple and red lines, respectively. A Gaussian filter is applied with $\sigma = 5$ years (darker blue, red, and purple lines), and bootstrapped 95% confidence intervals are shaded.)
HCW environments, in agreement with Brooks et al. (2003a) and Gensini and Ashley (2011). The change in annual days in future 30-year periods (2011–2040, 2041–2070, and 2071–2100) relative to the historical period are shown in (b), (e), (h) for RCP4.5, (c), (f), (i) for RCP8.5, and the difference between the RCP scenarios (RCP8.5 minus RCP4.5; (d), (g), (j)) for Figures 2.5–2.9. The stippling indicates where the distribution of the annual mean values are statistically significantly different at the 95% confidence level, computed using the Mann-Whitney-Wilcoxon test. Spatially, the areas depicted by both RCP4.5 and RCP8.5 as having the largest absolute increases in the future periods of the 21st century are very similar, though differences in the magnitude begin to emerge within the 2041–2070 period, though the largest statistically significant changes between the two forcing pathways become evident within the last 30 years of the century. This is in agreement with the trends evident within the annual anomalies presented in Figure 2.3.

Visually, the areas of largest absolute increase in frequency depicted by RCP8.5 for NDSEV, NDSEV_{1,6}, and STP highlight the northern Plains and the Southeast regions. In fact, these regions experience the largest absolute increases in the number of days with HCW favorable environments relative to other locales for all parameters except for MLCAPE, where the southern Plains region experiences the greatest regional mean increase of over 33 days per year (Table 2.2). In relative terms, when considering higher thresholds of NDSEV (i.e., NDSEV_{sig} and NDSEV_{tor}), the GCM shows a larger proportionate inflation of HCW days as compared to lower thresholds. As a result, this suggests that not only may the frequency of HCW days rise, but also the magnitude of the environmental parameter as well. On the comparison of NDSEV and NDSEV_{1,6} which weight S06 differently when combined with CAPE, it is noted that both parameters highlight the same areas, but differ only in their magnitude of increase. This supports the conclusions of Seeley and Romps (2015) and Paquin et al. (2014) that the overall qualitative results from these two quantities are in good agreement, and the magnitude differences are relatively small. In terms of days with large CAPE, undoubtedly, the greatest relative increases occur for all
areas of the CONUS east of the Continental Divide, with increases of 800 to nearly 5000%.

Figure 2.4. Mean annual number of (a) NDSEV$_{1.6}$ days and the mean departure for future 30-year periods (2011–2040, 2041–2070, and 2071–2100)) for RCP4.5 (b),(c),(h), RCP8.5 (c),(f),(i), and the difference between the two future scenarios (RCP8.5 minus RCP4.5; (d),(g),(j)). Stippling represents where the distribution of yearly mean values are significantly different at the 95% confidence level.
Figure 2.5. As in 2.4, but for NDSEV days.
Figure 2.6. As in 2.4, but for $NDSEV_{sig}$ days
Figure 2.7. As in 2.4, but for $NDSEV_{tor}$ days
Figure 2.8. As in 2.4, but for STP days.
Figure 2.9. As in 2.4, but for days with MLCAPE $\geq 2000 \text{ Jkg}^{-1}$. 
The addition of STP allows for insight into where favorable severe ingredients (CAPE, S06) occur in tandem with favorable low-level parameters (i.e., low LCL heights and high 0-1 km SRH), which may be indicative of environments more conducive to the formation of tornadoes. Results do not highlight any different areas, but rather simply hone in on those areas already identified as favorable for HCW. In terms of STP and NDSEV\textsubscript{tor}, both accentuate the northern Plains and Southeast regions as the two areas with the strongest increase by the end of the 21st century for both forcing pathways.

Table 2.2
Annual mean absolute change in parameter days for the RCP8.5 scenario for 2071–2100 as compared to 1971–2000.

<table>
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<th>Parameter</th>
<th>CONUS</th>
<th>ECONUS</th>
<th>Midwest</th>
<th>Northeast</th>
<th>Southeast</th>
<th>West</th>
<th>S. Plains</th>
<th>N. Plains</th>
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Table 2.3
Same as in 2.2 except for relative change (in %).

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When considering changes in mean annual frequency, it is also of question how the areal coverage of favorable environment days may be influenced in a warmer climate.
To investigate this problem, the size of a day, or in other words the areal coverage of favorable environmental conditions, is determined as the fractional coverage of U.S. land grid points east of -105°W that exceed the minimum parameter threshold. Results are evaluated for the 30-year historical period and the last 30 years of the model simulations for RCP4.5 and RCP8.5. In general, it is found that both future scenarios depict distributions of areal coverage that tend to be larger than that for the historical period, as shown by the shift upward in the median, interquartile range, and upper extremes for each parameter in Figure 2.10 (a)–(d). The distribution of daily sizes for all HCW environment days examined have been found to be statistically significant from one another at the 95% confidence level when tested with both the Mann-Whitney-Wilcoxon test and the two sample Kolmogorov-Smirnov (K-S) test, such that it may be said that the fractional area values for each simulation are likely not drawn from the same distribution.

Given that the minimum threshold is met for each parameter, the distribution of daily maximum values of that parameter can then be examined. The distribution of intensity for \(\text{NDSEV}_{1.6}, \text{NDSEV}, \text{STP}, \text{and MLCAPE}\) are illustrated by box plots in 2.11 (a)–(d), respectively. Only the minimum threshold for \(\text{NDSEV}\) is shown here as the distribution includes the higher thresholds. As illustrated, the intensity of each parameter depicts that the values become skewed toward more intense for both future scenarios. Again, the null hypothesis that the values for each scenario are drawn from the same distribution is rejected at the 95% confidence level.
Figure 2.10. Box plots depicting the distribution of fractional proportion of CONUS land points east of -105°W land points for (a) \(NDSEV\), (b) \(NDSEV\), (c) \(NDSEV_{sig}\), (d) \(NDSEV_{tor}\), (e) \(STP\), and (f) \(MLCAPE\). Historical distributions are for the years 1971–2000 and RCP4.5, and RCP8.5 scenarios for 2071–2100.
Figure 2.11. Box plots depicting the distribution of daily maximum parameter values for days exceeding the minimum threshold for the Historical, RCP4.5, and RCP8.5 experiments. Historical distributions are for the years 1971–2000 and RCP4.5, and RCP8.5 scenarios for 2071–2100.
2.3.2 Annual Cycle

It has been shown that the overall annual occurrence of favorable HCW environments is projected to rise in both future scenarios examined for GFDL-CM3 projections. In this section, a closer examination will investigate the annual cycle of the convective ingredients and favorable environments to assess when and where changes are occurring during the calendar year. As the two future scenarios do not become significantly different until after the mid-21st century, the 2071–2100 period will be the focus of analysis.

Seasonal Changes

The number of days with favorable HCW environments \( (NDSEV_{i.6}, \ NDSEV, \ NDSEV_{sig}, \ NDSEV_{tor}, \ and \ STP) \) undergo statistically significant increases for all four seasons (DJF, MAM, JJA, SON) under both RCP4.5 and RCP8.5 emission pathways. In general, just as seen for the mean annual frequency changes (Figures 2.4–2.8), both forcing pathways indicate similar areas of increase, where the magnitude of change presents the main difference. During the winter months of December, January, and February (DJF), all HCW parameters indicate the largest increase in favorable frequency in the southeastern portions of the U.S. (Figure 2.3.2), with the strongest response given by the RCP8.5 projection. Of note is the relative northward expansion of increase for each parameter, with the greatest changes farther north suggested by RCP8.5. \( NDSEV, \ NDSEV_{i.6}, \ and \ STP \) all indicate statistically significant increases in the western U.S also, especially along the Pacific coast.

In the spring months (MAM), both \( NDSEV_{i.6} \) and \( NDSEV \) departures from the historical mean highlight nearly the entire U.S. as undergoing increase in the number of days, for both future scenarios during the 2071–2100 period, averaging an increase approximately 4–4.5 (RCP4.5) to 7–8 (RCP8.5) days with more favorable MAM environments per year in the eastern U.S. For \( NDSEV_{sig} \) and \( NDSEV_{tor} \), and \( STP \), however, the largest inflation of days are confined to the eastern two-thirds
of the CONUS, with mean increases of 3.4 (6.2), 2.4 (4.5), and 2 (3.3) for days RCP4.5 (RCP8.5), with larger regional increases in both the southern Plains and the Southeast. A notable distinction from the historical period is the expansion further north and east of favorable springtime increases in all HCW parameters, such that a larger portion of the eastern U.S. becomes more favorable for HCW more often.

The most robust maximum increases in HCW environments materialize during JJA, with each parameter in Figure 2.3.2 accentuating the north central portion of the CONUS. Statistically significant changes in STP days are largely restricted to the northern Plains and portions of the Great Lakes region. Both NDSEV_{1.6} and NDSEV (albeit to a lesser extent), feature statistically significant decreases in the southwestern U.S. Further east, a reduction in NDSEV_{1.6} days occurs in a similar area with no statistically significant change in NDSEV, perhaps indicating that a reduction in S06 plays a larger role in those areas. Also particularly noticeable is the northward and westward shift of favorable environments, such that the centroid of maximum seasonal occurrence for all parameters, except for NDSEV_{tor}, has shifted about 1–2° in both latitude/longitude to the north and west.

The mean NDSEV_{1.6} departures in the future autumn period (SON) are the weakest compared to the other seasons, with an eastern CONUS mean increase of ∼1 (RCP4.5) and ∼2.5 (RCP8.5) days (roughly a 23% and 50% increase). The increases depicted by NDSEV_{1.6} and NDSEV are less consistent, more so in the RCP8.5 scenario, with NDSEV noting greater increases in the southeast U.S. than NDSEV_{1.6}; this may be due to the stronger weighting of S06, as the mean increases in CAPE occur in locations with a larger weakening of mean S06 (discussed shortly, see Figures 2.16 and 2.17). Regionally, the greatest mean increases occur in the northern Plains, Midwest, and Northeast regions across all HCW days, though largest increases in MLCAPE days are largely confined to the central United States.

While not an HCW indicator per se, the increase in frequency of days with large CAPE (MLCAPE ≥ 2000 Jkg⁻¹) undergoes a large increase by the end of the 21st century as indicated in Figure 2.9. Little to no statistically significant increases of big
Figure 2.12. Changes in DJF mean annual days for RCP4.5 (a,c,e,g,i) and RCP8.5 (b,d,f,h,j) for NDSEV$_{1.6}$, NDSEV, NDSEV$_{sig}$, NDSEV$_{tor}$, STP, respectively. Stippling indicate where differences are statistically significant at the the 95% confidence level.
Figure 2.13. Same as Figure 2.3.2, except for MAM.
Figure 2.14. Same as Figure 2.3.2, except for JJA.
CAPE days are noted in DJF, but each of the other seasons experience considerable increases determined to be statistically significant. It is readily apparent that the highest surge in additional $MLCAPE$ days are confined to the summer season within the north-south corridor of the central U.S. (Figure A.1). In fact, the average increase in the eastern two-thirds of the U.S. experience an increase of nearly 21 extra days with large CAPE during JJA, with some portions of the northern Plains expressing as many as 30–40 additional days as demonstrated in the RCP8.5 projection. Given these results, it is very evident that values of CAPE undergo significant modification under future climate scenarios.

As described in the previous chapter, thermodynamic changes such as warming of low-level temperatures and a corresponding increase in moisture (via the Clausius-Clapeyron relationship) may strongly influence CAPE in the future. Indeed, under both the RCP4.5 and RCP8.5 scenarios, statistically significant increases in near-surface temperature and specific humidity are evident across all seasons during the 2071–2100 period (Figures A.2 and A.3, respectively). Each of these model scenarios depict strongest increases in temperature and moisture during the warm season, with the RCP8.5 scenario projecting the most robust increases, particularly in moisture. In many regions east of the Rockies, mean increases of over $6 \text{gkg}^{-1}$ in specific humidity are evident during JJA, with the most pronounced moisture enhancement occurring over the northern Plains region. This strong increase in moisture may be related to the projected strengthening of the Great Plains low-level jet (GPLLJ), an important component of the summertime large-scale circulation responsible for transporting water vapor northward from the Gulf of Mexico into the central U.S. (Cook et al., 2008; Maloney et al., 2014).

Much of the increases in HCW days are likely driven by increases in CAPE, as statistically significant increases occur in both projections of late 21st century seasonal means (see (a), (d), (g), (j) of Figures 2.16 (RCP4.5) and 2.17 (RCP8.5)). Again, the changes illustrated by RCP8.5 are much more aggressive than the RCP4.5 scenario across all seasons, with the most intense intensification in mean CAPE values ($\geq 1000$
$Jkg^{-1}$ projected to occur in the northern Plains during JJA, which is very much aligned with the strong moisture response shown in Figure A.3(f). But while CAPE intensifies, the overall mean values of S06 and CIN decrease and increase, respectively, though the sign and magnitude differences are realized differently on a regional basis. For example, during DJF and MAM, the far southwestern U.S. experiences increases in S06 ((b) and (e) of Figures 2.16 and 2.17), while the northern tier of states along the Canadian border and states along the Atlantic seaboard experience a weak reduction in mean deep-layer shear which is only statistically significant during MAM. In the summer months, the strongest CAPE increases occur in areas where S06 and CIN undergo relatively weaker decreases and increases, accordingly. The largest reduction in mean S06 comes during the season that experiences the largest increases in CAPE. Statistically significant increases in CIN occur across all seasons from both scenarios, while again JJA undergoes the strongest absolute increases, particularly in the southern and central Great Plains. SON exhibits a robust decrease in S06 for many portions of the country, particularly southern and eastern areas, that overlap areas that experience an increase in mean CAPE values. This may contribute to the relatively little change in HCW environments in the Southeast, indicated by $NDSEV_{1,6}$. 
Figure 2.15. Same as Figure 2.3.2, except for SON.
Figure 2.16. Changes in RCP4.5 mean values of CAPE (J kg$^{-1}$), S06 (m s$^{-1}$), and CIN (J kg$^{-1}$) for (a)–(c) DJF, (d)–(f) MAM, (g)–(i) JJA, and (j)–(l) SON compared to the historical period.
Figure 2.17. As in 2.16, except for RCP8.5.
While changes in the mean values are informative, it is the combination of parameters, namely CAPE and S06, which are important for considering HCW. The aforementioned uptick in HCW environments seem to indicate that the rise in CAPE values likely compensate for any reductions in S06 (i.e. S06 may be weaker, but still of sufficient magnitude), and given the requirement that CIN be less than $100 \ J kg^{-1}$, the modification of the latter two variables has not hindered the overall potential for increased HCW. Nonetheless, the joint distribution of CAPE with other favorable variables was performed to gain insight into the causative shift in HCW climatology. As in the findings of Diffenbaugh et al. (2013), the decreases in S06 are concentrated within the low CAPE portion of the joint distribution for each RCP scenario (Figure 2.18). As such, this decrease generally falls below the minimum threshold of NDSEV and well below the higher thresholds of the product of CAPE and S06; thus, little to no impact is evident upon the HCW environment days due to the mean decrease in S06. Similarly, the change in the joint probability distribution of CAPE and CIN demonstrates that though occurrence of large values of CIN in the presence of non-zero CAPE rises, the largest increases in CAPE seem to occur when CIN is at or below $100 \ J kg^{-1}$.
Figure 2.18. Mean seasonal changes in the joint probability distribution of CAPE and S06 for the eastern CONUS (east of -105°W, land points only) for (a),(d) DJF, (b),(e) MAM, (c),(f) JJA, and (d),(h) SON compared to the historical period. RCP4.5 differences are depicted in (a)–(d) while RCP8.5 are depicted in (e)–(h). The solid, dashed, and dashed-dot black lines indicate where in the parameter space NDSEV, NDSEV_{sig}, and NDSEV_{tor} thresholds are met. Stippling indicates where the differences are statistically significant.
Figure 2.19. Mean seasonal changes in the joint probability distribution of CAPE and CIN for the eastern CONUS (east of -105°W, land points only) for (a), (d) DJF, (b), (e) MAM, (c), (f) JJA, and (d), (h) SON compared to the historical period. RCP4.5 differences are depicted in (a)–(d) while RCP8.5 are depicted in (e)–(h).
Julian Date Analysis

In addition to seasonal means, analysis based upon Julian date allows for a finer temporal analysis of HCW environments. The probability of experiencing an HCW day anywhere in the eastern U.S. (east of -105°W, where HCW environments are mostly confined) for the historical 30-year period (navy blue line) and the future 30-year period for both RCP4.5 and RCP8.5 projections were tabulated. The probabilities of experiencing a \( NDSEV_{1.6} \), \( NDSEV \), \( NDSEV_{sig} \), \( NDSEV_{tor} \), \( STP \), and \( MLCAPE \) days are shown in Figure 2.20(a)–(f). As evidenced by the Julian day probabilities, the greatest probability increases are generally seen in the tails of the annual probability distribution. In general, a widening of the probability suggests that there will be an earlier start and a later ending of the typical severe season in future periods. This conclusion is supported by examination of the mean empirical cumulative distribution function (CDF) of HCW environment days for the future and the historical periods. For example, the mean empirical CDF for \( NDSEV_{sig} \) days is demonstrated in Figure 2.21 for each projection. If the beginning of the severe season is subjectively determined to begin when 20% of the total annual environment days are accumulated and ends at 80%, then the season is, on average, lengthened anywhere from 9–31 days, depending on parameter and RCP scenario (see Table 2.4). The earlier accumulation of days is much more pronounced at higher thresholds of the CAPE/S06 product (i.e., \( NDSEV_{sig} \) and \( NDSEV_{tor} \)) compared to other HCW parameters, and the RCP8.5 emissions scenario demonstrates a much more marked change relative to RCP4.5. These results support the notion that there may be a greater likelihood for favorable HCW environments to occur both earlier and later in the annual cycle, effectively lengthening the HCW season, supporting previous results of Lee (2012) and Van Klooster and Roebber (2009). Given that CAPE increases for all seasons, it comes as no surprise that a lengthening of the season may occur, due to the fact that increases in CAPE values during the cool seasons come at a time when larger values of S06 are more often present.
Mean differences in days for several percentiles of the empirical CDFs shown in Figure 2.21.

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<td>15</td>
<td>19</td>
</tr>
</tbody>
</table>
Figure 2.20. 30 year mean probability estimates of an environment day anywhere in the U.S. east of -105 °W (land points only) by Julian day for (a) $NDSEV_{1.6}$, (b) $NDSEV$, (c) $NDSEV_{sig}$, (d) $NDSEV_{tor}$, (e) $STP$, and (f) $MLCAPE$ days. The raw probabilities are represented by the scatter points, and a Gaussian filter is applied with $\sigma = 15$ days, as in Brooks et al. (2003a), represented by the bold lines. The historical period (1971–2000) is represented by the navy blue line, and RCP4.5 and RCP8.5 scenarios (2071–2100) are represented by the purple and red lines, respectively.
Figure 2.21. Comparison of the mean empirical CDF of NDSEV_{sig} days between the historical (solid line) and future (dashed line) periods for (a) RCP4.5 and (b) RCP8.5 scenarios. Bootstrapped 95% confidence intervals are shaded (blue: historical, red: future).
2.4 Summary

In summary, this chapter examined the response of future convective environments projected by the GFDL-CM3 global climate model under both the RCP4.5 and RCP8.5 scenarios. From the analyses presented, it became apparent that the two climate projection scenarios do not significantly diverge from one another until after the middle of the 21st century, primarily driven by the more aggressive increases in CAPE by RCP8.5. Both future scenarios demonstrate similar spatial patterns in their projected increases, though RCP8.5, comparatively, is much more bullish in terms of magnitude changes. In fact, the future projections depicted by GFDL-CM3, are the most aggressive of all the models Seeley and Romps (2015) examined. By the last 30-year period of the century (2071–2100), the largest absolute increases in HCW activity occur in MAM and JJA, though the largest relative differences occur in DJF. Both scenarios highlight two areas of greatest annual increase in days favorable HCW environments: the northern Plains and the Southeast. For the former, the changes manifest during JJA in the area with most significant increases in CAPE, while the latter materializes earlier in the annual cycle. This is likely due to rising CAPE values during the early part of the year when strong S06 are more often present, resulting in an enhanced frequency of HCW environments. During both DJF and MAM, the area exposed to favorable HCW environment expands, and the location of maximum JJA recurrence shifts further north and west. In accordance with previous work, it was found that overall, the sensitivity of S06 weighting within the \( NDSEV_{1.6} \) and \( NDSEV \) formulations does not impact the overall qualitative interpretation of changes on HCW environments, in agreement with previous findings (Seeley and Romps, 2015; Paquin et al., 2014).

An important result of this environmental analysis demonstrates that days with favorable atmospheric conditions for severe thunderstorms are increasing in their areal coverage. In addition to the greater extent in HCW day size, the intensity of each parameter rises for both future scenarios, largely attributed to future increases in
CAPE. As a result, more frequent days with favorable HCW environments are projected by the end of the 21st century. Moreover, the evaluation of the annual cycle of HCW environments provides evidence that the severe thunderstorm season may be lengthened in future climate.
CHAPTER 3. HIGH-RESOLUTION DYNAMICAL DOWNSCALING

3.1 Introduction

The method of analyzing the large-scale environmental conditions conducive for HCW, or implicit modeling approach, lends great insight into potential changes in frequency, intensity, and seasonality of severe storms in the future. Nevertheless, while HCW occurrences are strongly tied to large scale atmospheric conditions, the implicit method remains an overestimate of potential HCW changes due to the inability to account for whether or not severe storms will develop within a favorable environment. In particular, it is unclear how modulation of atmospheric features and processes which may lead to convective initiation may be impacted within a future climate. To better address this question, this study acts upon the recommendation of previous work to use high-resolution (4-km), convection-permitting simulations of future climate to better address the question of HCW impacts due to anthropogenic climate change. This chapter will first describe the regional climate model and general methodology for creating such a dataset. Next, borrowing techniques used for mining severe weather guidance from short-term, high-resolution forecasts, estimations of HCW occurrence under future climate will be made. Lastly, it is hypothesized that this approach may allow for greater understanding of potential impacts upon individual hazard types (i.e. hail, wind, and tornadoes).

3.2 Data and Methods

3.2.1 Regional Climate Model

The WRF-ARW version 3.6 will herein act as the regional climate model (RCM) to dynamically downscale the GFDL-CM3 under historical and RCP8.5 conditions
(r1i1p1 realization member). Initial and boundary conditions for WRF are supplied by the 6-hourly GCM data for the large-scale atmospheric fields, daily snow cover and sea ice fraction, and monthly average soil parameters (temperature and moisture) and sea surface temperatures. The 3-D atmospheric variables are interpolated from the hybrid vertical coordinates to pressure levels. Monthly average soil moisture was converted to volumetric soil moisture fraction, and along with soil temperature, were interpolated to 0–10 cm, 10–40 cm, 40–100 cm and 100–200 cm depth averages.

A single computational domain encompassing the entire continental U.S. at convection permitting spatial resolution (4-km grid spacing, no cumulus parameterization) will serve as the region of study (Figure 3.1). Following the methodology of Trapp et al. (2007a,b), Robinson et al. (2013), Gensini et al. (2014a), and Gensini and Mote (2015), it was determined that intermediate nesting was not required to transition between coarse boundary conditions, despite the large resolution jump between the GCM and RCM. A 10 point buffer zone is applied at the lateral boundary (Davies and Turner, 1977), as is common in regional climate modeling, to provide a smoother transition at the lateral boundaries between the coarser boundary conditions and the model solution (Giorgi and Mearns, 1999; Gula and Peltier, 2012). There is still debate as to the horizontal grid spacing that can be used without a cumulus parameterization, though 4-km is generally accepted (e.g., Weisman et al., 1997). Simulations will be performed both a historical (1971–2000) and future (2071–2100) time period, using the historical and RCP8.5 CMIP5 experiments, respectively. The annual simulations are a significant departure from previous downscaling efforts that focus simply upon the warm season months when severe weather frequency traditionally peaks. Specific information regarding model configuration, including choice of parameterizations, may be found in Table 3.1. The choice of microphysics (Thompson), longwave (Rapid Radiative Transfer Model; RRTM) and shortwave radiation (Dudhia), and surface and planetary boundary layer (Mellor-Yamada-Nakanishi-Niino; MYNN) parameterization schemes were largely motivated by their implementation into version 2 of the operational Rapid Refresh (RAP) and High-Resolution Rapid Refresh (HRRR)
short-range weather forecasting models (Benjamin et al., 2015). The RAP and HRRR forecasts are often used as guidance for rapidly evolving weather events, such as severe thunderstorms (Benjamin et al., 2015). Moreover, it has been shown by Coniglio et al. (2013) that the MYNN PBL scheme was nearly biased in terms of moisture, potential temperature, and PBL depth in pre-convective environments as compared to other schemes. Additionally, the Thompson microphysics scheme has been documented as being able to realistically capture the trailing stratiform region of simulated mesoscale convective systems (Wheatley et al., 2014; Morrison et al., 2015). Lastly, the trace gas concentrations were kept fixed for both the historical and future runs. While the effect of this omission is unknown, it is hypothesized that any changes would only be minor relative to the larger scale atmospheric forcing, especially when considering the integration procedure employed in this study (to be discussed shortly).

To develop a historical baseline climatology, the historical experiment will be used to examine past climate. For future climate, the most aggressive RCP8.5 scenario will be utilized to maximize signal detection of any possible changes that may occur due to “business as usual” characteristics. It should be noted that this is meant to represent a likely extreme in the future, and should not be interpreted as a selection of the most likely future outcome.

Simulation data output were post-processed using the Unified Post-Processor (UPP) version 2.2 and converted to GRIdded Binary version 2 (GRIB2) format using custom Python scripts. The conversion to GRIB2 from the raw, uncompressed NetCDF format files output directly from WRF significantly reduces file size by approximately 70%. The GRIB2 table may be found in Table D.1.

The procedure for downscaling will involve a succession of daily initialized (06 Z) 30-hour WRF model integrations with hourly data output. The first 6 forecast hours of integration will be considered a model spin-up period (Skamarock, 2004) and disregarded such that the model forecast is valid for a period 24 hour period between 1300Z–1200Z. This short overlap period is meant to remove the spin-up effects during this period prior to computing climate statistics (e.g., Kotlarski et al., 2012; Lucas-
Picher et al., 2013), which is slightly different than the approach of Trapp et al. (2011) and Robinson et al. (2013). In this sense, the method of downscaling treats the regional climate as a collection of short-range forecasts, essentially a combination of types 1 and 4 downscaling Castro et al. (2005).

There are several advantages and disadvantages to the frequent re-initialization approach in regional climate modeling. While common in the numerical weather prediction community, the frequent re-initialization approach is still not as widely prevalent as continuous integration in regional climate modeling. Despite this fact, it has been shown that frequent re-initialization can improve the sequence of weather events in simulations, increase the spatiotemporal simulation of precipitation patterns, and prevent significant drift away from the large-scale conditions within the parent model (Pan et al., 1999; Qian et al., 2003; Lo et al., 2008; Kotlarski et al.,...
Table 3.1
WRF configuration information.

<table>
<thead>
<tr>
<th>Parameterizations</th>
<th></th>
</tr>
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<tbody>
<tr>
<td>Microphysics</td>
<td>Thompson (Thompson et al., 2008)</td>
</tr>
<tr>
<td>Radiation (LW/SW)</td>
<td>RRTM/Dudhia (Mlawer et al., 1997; Dudhia, 1989)</td>
</tr>
<tr>
<td>Land surface</td>
<td>Noah (Chen and Dudhia, 2001)</td>
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</table>

<table>
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<th>Model Parameters</th>
<th></th>
</tr>
</thead>
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<td>Domain size</td>
<td>750 x 1150 horizontal grid points</td>
</tr>
<tr>
<td>Vertical levels</td>
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</tr>
<tr>
<td>Time step</td>
<td>adaptive</td>
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<td>Specification zone/relaxation zone</td>
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</tr>
</tbody>
</table>

<table>
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<th>Initial/Boundary Conditions</th>
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</thead>
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</tr>
<tr>
<td>geopotential height, U and V wind,</td>
<td></td>
</tr>
<tr>
<td>surface pressure</td>
<td></td>
</tr>
<tr>
<td>Soil temperature, soil moisture</td>
<td>0–10, 10–40, 40–100, 100–200 cm</td>
</tr>
</tbody>
</table>

2012; Lucas-Picher et al., 2013). As a result, the driving model maintains a strong influence over the downscaled simulation allowing for greater consistency between GCM and the RCM simulation. Hong and Kanamitsu (2014) advocate for the frequent re-initialization or spectral nudging approach to limit error growth within the domain. While more computing time is required owing to overlapping 6 hour periods to account for spin-up, the method allows for a large number of simulations to be executed simultaneously. Perhaps the largest drawback of the frequent re-initialization approach arises due to the frequent updating of the land surface variables (e.g., soil moisture). Soil variables are slow to spin-up and may require a season to several years to reach equilibrium (e.g., Giorgi and Mearns, 1999); however, it has been suggested
the effects of long memory processes such as soil moisture may be of secondary importance to atmospheric forcing (Pan et al., 1999). Additionally, Robinson (2012) found that continuous integration over a three month time period resulted in a dry bias in soil moisture which reduced precipitation amounts, a similar finding to Xue et al. (2007). It is also assumed that these processes are being handled adequately by the GCM land surface model, though feedbacks from the higher-resolution simulation are not taken into account. Furthermore, the one-way nesting approach does not account for any upscale feedbacks from the regional domain to the larger scale environment used for initial and boundary conditions.

3.2.2 Estimating HCW Events from Model Output

The high-resolution WRF simulations cannot directly resolve tornadoes or other small-scale convective features, and thus the use of model proxies will be used to estimate the occurrence of a simulated severe weather hazard such as large hail, damaging wind, and/or tornado. Recent work in the severe storms community have developed severe storm “proxies” or “surrogate” severe weather reports to mine information regarding model predicted storm attributes and their potential use for prediction of severe weather hazards such as large hail, damaging wind, and tornadoes (e.g., Kain et al., 2008, 2010; Sobash et al., 2009, 2011; Carley et al., 2011). Perhaps the most common proxy variable used is updraft helicity (UH). UH, as defined by Kain et al. (2008), is the vertically integrated product of the updraft velocity \( w \) and vertical vorticity \( \zeta \),

\[
UH = \int_{z_b}^{z_t} w \zeta \, dz \tag{3.1}
\]

where \( z_b \) and \( z_t \) generally refer to 2 km and 5 km AGL levels, respectively. The UH quantity is often used to identify mid-level mesocyclones and therefore is often considered a proxy for supercell detection (e.g., Kain et al., 2008, 2010; Sobash et al., 2009, 2011; Carley et al., 2011; Jirak et al., 2010). In more specific terms, UH de-
scribes the spatial correlation between the updraft and rotation. In supercell storms, this correlation arises through a multi-step process. In the initial stages of supercell development, interaction between the updraft and vertical wind profile causes tilting of the environmental shear vector by the updraft. This produces two counter-rotating vortices on either side of the updraft, resulting in a net updraft circulation of zero. Nonlinear rotational effects lead to splitting and deviant motion. As a consequence, the storm begins to ingest streamwise vorticity and acquires net cyclonic rotation as the cyclonic member is advected into the updraft by the storm relative winds (Davies-Jones, 1984). While quasi-linear convective systems may produce tornadoes and severe hail, by and large their largest associated threat is typically damaging winds ((Gallus et al., 2008, e.g.,)). Linear systems can also be associated with rotating updraft cores, however, lower thresholds of UH will likely need to be used as the rotation typically exists over a shallower depth and is weaker, comparatively (Weisman and Trapp, 2003).

The combination of UH and simulated radar reflectivity exceeding specified thresholds has been a common proxy for severe weather occurrence and shown to sufficiently capture the spatial and temporal distribution of observed severe weather occurrences (Trapp et al., 2011; Gensini et al., 2014b; Gensini and Mote, 2015). Updraft helicity is a useful surrogate for supercell detection, and thus all hazards associated with that mode. However, using this proxy Trapp et al. (2011); Robinson et al. (2013); Gensini et al. (2014b) found overall severe occurrences were not captured going into the summer months, particularly in the eastern U.S. This result is likely attributed to wind occurrences not detected by UH due to the non-association of such events with a supercellular mode of convection. Thus, especially when considering marginal HCW occurrences, UH may not be the most suitable proxy. Alternatively, updraft vertical velocity (UVV) may be used as a measure of storm intensity, with a greater updraft indicating a greater potential for severe thunderstorm occurrence. Because not all severe storms rotate, it is hypothesized that this variable may better capture HCW events associated with all modes of convection. As a result, we will use hourly
maximum values of UH (hereafter referred to as maxUH) and hourly maximum UVV (maximum updraft vertical velocity in the lowest 400 hPa) as proxies for a general severe weather occurrence. Instead of values valid at the top of the hour, hourly maximum values (Kain et al., 2010, e.g.,) will be used such that strong values that occur between hourly output times are not disregarded, allowing for storm-attribute parameters at a higher temporal frequency to be taken into account.

The next question becomes at which threshold values must these proxy values meet in order to be considered an HCW occurrence. Many HCW proxies used in the literature are grid-spacing dependent (e.g., many rely on horizontal derivatives) and may be influenced by choice of physics parameterization schemes. Similar to Sobash et al. (2009, 2011), a distribution based approach was used to decide the minimum threshold; the 99.95 percentile of non-zero values was chosen to serve as the lower threshold for severe values, which approximately equates to 50 m$^2$s$^{-2}$ and 20 ms$^{-1}$ for maxUH and UVV, respectively. The former corresponds closely to the minimum thresholds used in previous work.

In addition to these two variables, exploratory analysis of the response of other model output variables which may be able to distinguish between the occurrences of specific hazards will be performed. Such variables include hourly maximum 10-m wind speed (maxWIND; ms$^{-1}$) and column maximum vertically integrated graupel (maxGRPL; kg m$^{-1}$ or mm of liquid equivalent), which may provide indication as to severe convective wind gusts and hail occurrences (Kain et al., 2010). For wind and hail estimation, a distribution based lower threshold was chosen as for maxUH and UVV, such that the 99.95 percentile values for maxWIND and maxGRPL corresponds approximately to 20 ms$^{-1}$ and 25 kg m$^{-2}$, respectively. To eliminate high-wind events that are non-convective in nature, it was required that at least 40 dBZ in the hourly maximum 1-km AGL simulated reflectivity be present.

Moreover, new experimental diagnostics developed by the Air Force Weather Agency (AFWA) to estimate hail size and tornado wind speed will be examined (Creighton et al., 2014). Each of these parameters combine storm-scale and environ-
mental data, and uncertainty information is provided via a Weibull distribution for the cumulative distribution function (CDF). From the CDF, defined as

\[ CDF(X) = 1 - e^{\left(\frac{x-x_0}{\beta}\right)^\alpha} \]  

(3.2)

the probability of exceedance of some threshold \( X \) is determine by subtracting the CDF value from one. \( X_0 \) represents the numeric value output from the respective algorithms, which is taken to be an estimate of the median expected value (E. Kuchera 2016; personal communication), and \( \beta \) and \( \alpha \) are empirically defined for each diagnostic. The hail size parameter (AFWAhail; mm) takes into account a measure of the hail size which may be supported by the updraft, low-level temperature information to allow for melting of hail as it reaches the surface, an estimate of dry air entrainment (via relative humidity) in the mid-levels which may lead to size sorting, and lastly, an updraft helicity term is included as a measure of potential hail growth due to a mesocyclone. All combined, the AFWAhail diagnostic is defined as follows:

\[ \text{AFWAhail} = \left( \text{Updraft} - \text{Melt} - \text{MidRH} \right) \times \text{Duration} \]  

(3.3)

where

\[ \text{Updraft} = \frac{\text{Vertical Velocity}(ms^{-1})}{1.4} \times 1.25 \]  

(3.4)

\[ \text{Melt} = 2 \text{ m Temperature (K)} - 288.15; \text{ min of 0} \]  

(3.5)

\[ \text{MidRH} = 3.5 \text{ km AGL RH (%)} - 70.0; \text{ min of 0} \]  

(3.6)

\[ \text{Duration} = \frac{2-5 \text{ km UH}}{100} + 0.25 \]  

(3.7)

The designated parameters for the Weibull distribution are \( \alpha = 1.5 \), \( \beta = 0.9 \times \) AFWAhail, and \( X_0 = \text{AFWAhail} - \beta \). For a median expected value of 25 mm, the
The probability of exceeding a hail size of greater than 25 mm is approximately 37%, and 57% and 74% for AFWA_hail values of 35 and 50 mm accordingly.

The tornado wind speed parameter involves measures of updraft helicity such that higher values of the diagnostic will be indicated when there is updraft helicity in the presence of favorable environmental characteristics.

\[
\text{AFWA}_{\text{tor}} = 50 \times \text{Supercell} \times \text{LLbuoy} \times \text{LLshear} \times \text{MidRH}
\]

(3.8)

where the Supercell, LLbuoy, LLshear, and MidRH terms are defined as:

\[
\text{Supercell} = \frac{2-5 \text{ km Updraft Helicity (m}^2\text{s}^{-2}) - 25}{50}; \text{ min 0, max 1}
\]

(3.9)

\[
\text{LLbuoy} = \frac{3000 - \text{LFC height (m)}}{1500}; \text{ min 0, max 1}
\]

(3.10)

\[
\text{LLshear} = \frac{0 - 2000 \text{ m wind shear (ms}^{-1}) - 2}{10}; \text{ min 0, max 1}
\]

(3.11)

\[
\text{MidRH} = \frac{90 - 3.5 \text{ km AGL RH (})}{30}; \text{ min 0, max 1}
\]

(3.12)

The corresponding Weibull parameters are \(\alpha = 1.0, \beta = 0.5 \times \text{AFWA}_{\text{tor}},\) and \(X_0 = \text{AFWA}_{\text{tor}} - \beta.\) As an example of the interpretation of these values, a median expected value of 40 m\(s^{-1}\) would indicate that the probability of exceeding a tornadic wind speed greater than EF0 intensity (approximately 30 m\(s^{-1}\)) would be 64%, and a 22% chance of exceeding EF-2 wind speeds of greater than 50 m\(s^{-1}\). The inclusion of the Supercell (UH) term tests for the presence of a rotating storm, the low-level buoyancy term attempts to delineate between elevated and surface based supercells, where the latter has a much greater probability of becoming tornadic. The final two terms were incorporated simply based upon their empirical relationship with tornado formation. Despite the potentially problematic approach of evaluating environmental conditions in the vicinity of a modeled storm, higher values of the AFWA parameters will indeed be indicated when favorable environment values are collocated with the storm. This
means that the AFWAtor values, for example, will be higher when UH values occur in the presence of favorable environment values. As a final note, it is emphasized that these measures are simply exploratory in nature, and are used primarily to gauge their response to future conditions. Literature relating storm-scale proxies as surrogates for severe weather reports have mostly focused on updraft helicity as a singular proxy for all hazards, and less work has been done to evaluate the performance of hazard type proxies relative to observed reports. In particular, the AFWA diagnostics were empirically derived, and “No attempts were made to calibrate against real data, and verification was pretty minimal as well.” (E. Kuchera 2016, personal communication).

Grid point proxy occurrences (given a value of “1” if the specified threshold is exceeded while other points are given a value of 0) are aggregated within the latitude/longitude grid boxes defined by our interpolated GCM grid. While the size of the bounding box chosen is larger than is typically used (i.e., 40–80 km), it allows for the proxies to eventually be related back to the environmental controls analyzed in the previous chapter. Further, this method of coarsening the high resolution simulations may be considered a neighborhood, or “fuzzy” verification, approach for evaluating high-resolution spatial fields, whereby the observed and simulated proxies are upscaled to a coarser resolution to account for reasonable displacement errors (e.g., Ebert 2008; Gilleland et al. 2010). This is a common approach when attempting to verify small-scale features of high-resolution forecasts. As such, we can analyze the occurrence of proxy “days,” where a day describes the occurrence of at least one grid point within the coarsened grid box meeting the specified threshold over the 24-hour period between 1200–1200Z. Additionally, the frequency of grid point exceedances will be described in an effort to quantify the overall activity. Rather than analyzing the raw frequency, the grid point counts are normalized by the total number of grid points enclosed by the coarsened grid box. This methodology arises from the fact that due to differences in grid projection between the RCM and GCM, the number of RCM grid points contained within the geographic bounds are not consistent between all coarsened grid boxes. In this manner, a spatiotemporal climatology of both po-
Potential HCW days and spatial frequency can be created, though care must be taken in the interpretation of these frequency results. It becomes difficult to tease out the difference between coverage and frequency by use of this procedure. For example, if long swath of contiguous values pass within the coarsened box, this points to a larger coverage of activity, perhaps even due to a single storm. On the other hand, the same number of grid points may be activated but are more disjointed in location, perhaps indicating separate events. The speed at which the storm passes through the grid box also plays a role in the activation of grid points. Nonetheless, differences between occurrence in the historical and future climatological periods will be computed, and statistical significance of the results will use the Mann-Whitney-Wilcoxon test.

3.3 Results

3.3.1 Brief Evaluation of the Downscaled Historical Simulations

Comparing the dynamically downscaled RCM performance during the historical period to observational data allows for the assessment of the RCM ability to adequately capture the magnitude and spatiotemporal aspects of the climatology for different variables. This is an important step, as confidence in simulations of future climate are often based largely upon how well the current climate is captured (e.g., Wang et al., 2015). Due to the chosen integration procedure, it is not anticipated that the RCM will add value to the larger scale features, however, smaller scale influences from topography, coastlines, etc. may allow for more accurate simulation of climate at localized scales. However, many of these features will also be impacted by the choice of resolution and parameterization schemes used for the RCM simulations, and their effect is currently unknown.

A natural comparison between the observed and RCM performance at simulating near-surface temperature, dewpoint temperature, and the mean precipitation climatology may lend insight into the ability of the downscaled simulations to ad-
equately capture current climate. Observations for these variables were provided by
the Parameter-elevation Regressions on Independent Slopes Model ((PRISM; Daly
et al., 2008)) dataset, the official source of climatological precipitation and tempera-
ture data for the U.S. Department of Agriculture, available from Oregon State Uni-
versity (http://www.prism.oregonstate.edu/). The dataset is available upon a ∼4-km
grid which are then interpolated to the 4-km WRF grid. For comparison, PRISM
seasonal mean temperature and precipitation (1971–2000) and mean dewpoint tem-
perature (1981–2010) will be compared to the 1971–2000 mean from the downscaled
simulations. While the dew point temperature climatology uses a 30-year period
(1981–2010), the differences are likely not too great between the time periods to
draically alter the comparison. In general, the downscaled WRF simulations are
adequately able to capture the seasonal spatial pattern of seasonal mean temperature
\( T \) and dew point temperature \( T_d \) relative to the observations, with spatial corre-
lation values greater than 0.96 for the standardized anomalies, wherein standardized
anomaly values are defined as the departure from the spatial mean and normalized
by the standard deviation within the domain. This transformation allows for rela-
tive maxima/minima to be identified within the spatial field for ease of comparing
patterns. However, it is noted that there is a cool, dry bias for most areas across
all seasons, with a few exceptions such as the slightly moist bias in DJF and a few
regional departures (Table 3.2).

In terms of mean seasonal rainfall, as in Robinson et al. (2013), spatial correlation
for standardized anomalies (Figure 3.2) to assess the level of pattern correlation. Sea-
sonal correlation values between WRF and PRISM are listed in Table 3.3. Visually,
and supported by correlation values, the macro pattern of precipitation appears to
be captured fairly well for all seasons except JJA, though WRF tends to overesti-
mate precipitation totals (Table 3.4), a known characteristic of WRF simulations at
convection-allowing resolution (Weisman et al., 2008; Robinson et al., 2013). To rule
out the supposition that this bias is inherited from GFDL-CM3, precipitation values
from WRF are upscaled to the 1° GCM grid using an areal average method, and the
Table 3.2
Seasonal mean error (ME) in °C for temperature (T) and dew point temperature (Td).

<table>
<thead>
<tr>
<th>Region</th>
<th>DJF</th>
<th>MAM</th>
<th>JJA</th>
<th>SON</th>
<th>DJF</th>
<th>MAM</th>
<th>JJA</th>
<th>SON</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONUS</td>
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<td>-3.02</td>
<td>-2.15</td>
<td>-1.12</td>
<td>0.56</td>
<td>-1.15</td>
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<td>-0.51</td>
<td>1.92</td>
<td>-1.05</td>
<td>-2.30</td>
<td>-0.55</td>
</tr>
</tbody>
</table>

Spatial correlation between the standardized anomalies of mean seasonal precipitation were computed (see Figure 3.3). Similar to the previous comparison between PRISM and WRF, the GCM and RCM precipitation climatologies are once again most dissimilar during the summer months with near zero correlation for the states in the Southeast region. This result confirms that indeed this pattern arises only within the regional climate simulations.

To further investigate the precipitation results from the RCM simulations, the mean number of days within the season experiencing daily rainfall totals greater than a range of specified thresholds (0.25 mm, 10 mm, 25 mm, and 50 mm) were tallied. For comparison, the standardized anomalies are also displayed in addition to the days (Figure 3.4), which highlights that for each of these thresholds, the Gulf Coast states experiences higher occurrences relative to the entire CONUS domain. It is possible that the choice of configuration for the RCM, particularly the microphysical and planetary boundary layer (PBL) parameterization schemes, may play a stronger role in these results. McCaul et al. (2014) demonstrated that simulations of sum-
Figure 3.2. Standardized anomalies of mean seasonal precipitation (1971-2000) for the downscaled WRF simulations (top) and the PRISM dataset (bottom) for (a) DJF, (b) MAM, (c) JJA, and (d) SON.
mertime convection in the deep South forced by the sea breeze were sensitive to the combination of microphysics and PBL schemes in addition to the input land surface conditions. In terms of the latter, it was shown that drier soil conditions produced less convective precipitation, and that the sensitivity to the land surface conditions was

Table 3.3
Pattern correlation for standardized anomalies of seasonal mean precipitation between WRF and PRISM.

<table>
<thead>
<tr>
<th>Region</th>
<th>Annual</th>
<th>DJF</th>
<th>MAM</th>
<th>JJA</th>
<th>SON</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONUS</td>
<td>0.8564</td>
<td>0.8528</td>
<td>0.8939</td>
<td>0.6267</td>
<td>0.8202</td>
</tr>
<tr>
<td>Midwest</td>
<td>0.9526</td>
<td>0.9574</td>
<td>0.9696</td>
<td>0.3728</td>
<td>0.8814</td>
</tr>
<tr>
<td>Northeast</td>
<td>0.7938</td>
<td>0.8116</td>
<td>0.7369</td>
<td>0.3478</td>
<td>0.7183</td>
</tr>
<tr>
<td>Southeast</td>
<td>0.1184</td>
<td>0.5255</td>
<td>0.6893</td>
<td>0.153</td>
<td>0.0921</td>
</tr>
<tr>
<td>West</td>
<td>0.8701</td>
<td>0.8496</td>
<td>0.8341</td>
<td>0.8206</td>
<td>0.8875</td>
</tr>
<tr>
<td>S. Plains</td>
<td>0.8348</td>
<td>0.8448</td>
<td>0.9447</td>
<td>0.348</td>
<td>0.5601</td>
</tr>
<tr>
<td>N. Plains</td>
<td>0.8847</td>
<td>0.9091</td>
<td>0.8594</td>
<td>0.889</td>
<td>0.863</td>
</tr>
</tbody>
</table>

Table 3.4
Mean error of 1971–2000 mean seasonal precipitation (inches) from down-scaled WRF simulation as compared to PRISM.

<table>
<thead>
<tr>
<th>Region</th>
<th>Annual</th>
<th>DJF</th>
<th>MAM</th>
<th>JJA</th>
<th>SON</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONUS</td>
<td>8.62</td>
<td>2.02</td>
<td>3.37</td>
<td>1.98</td>
<td>1.26</td>
</tr>
<tr>
<td>Midwest</td>
<td>6.84</td>
<td>0.37</td>
<td>2.44</td>
<td>3.85</td>
<td>0.18</td>
</tr>
<tr>
<td>Northeast</td>
<td>6.73</td>
<td>0.159</td>
<td>3.10</td>
<td>2.64</td>
<td>0.83</td>
</tr>
<tr>
<td>Southeast</td>
<td>0.52</td>
<td>0.51</td>
<td>4.21</td>
<td>-4.11</td>
<td>-0.09</td>
</tr>
<tr>
<td>West</td>
<td>13.58</td>
<td>5.04</td>
<td>3.68</td>
<td>1.88</td>
<td>2.98</td>
</tr>
<tr>
<td>S. Plains</td>
<td>10.85</td>
<td>2.35</td>
<td>4.33</td>
<td>2.49</td>
<td>1.68</td>
</tr>
<tr>
<td>N. Plains</td>
<td>9.65</td>
<td>1.39</td>
<td>2.05</td>
<td>5.25</td>
<td>0.96</td>
</tr>
</tbody>
</table>
more pronounced than choice of microphysics and PBL parameterizations. Further, the divergence in precipitation pattern during the summer months likely arises due to the transition from stronger synoptic scale forcing to a more dominant mesoscale forcing by which convection originates. The strong summertime deficit in precipitation totals along the Gulf coastal states is concerning, as the sea breeze serves as a mechanism for frequent initiation of deep convection in these regions. Yet, it is not anticipated that this result would drastically impact the overall HCW climatology, with the exception of a few summertime severe wind occurrences in that region.

### Table 3.5

Pearson coefficient of linear correlation of mean standardized anomalies of precipitation between WRF and GFDL-CM3.

<table>
<thead>
<tr>
<th>Region</th>
<th>Annual</th>
<th>DJF</th>
<th>MAM</th>
<th>JJA</th>
<th>SON</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONUS</td>
<td>0.7887</td>
<td>0.8555</td>
<td>0.8190</td>
<td>0.7247</td>
<td>0.8122</td>
</tr>
<tr>
<td>Midwest</td>
<td>0.9394</td>
<td>0.9853</td>
<td>0.9758</td>
<td>0.6430</td>
<td>0.8502</td>
</tr>
<tr>
<td>Northeast</td>
<td>0.4452</td>
<td>0.7481</td>
<td>0.7445</td>
<td>0.3900</td>
<td>0.6412</td>
</tr>
<tr>
<td>Southeast</td>
<td>0.6701</td>
<td>0.4405</td>
<td>0.9237</td>
<td>-0.0169</td>
<td>0.4413</td>
</tr>
<tr>
<td>West</td>
<td>0.7467</td>
<td>0.7916</td>
<td>0.6854</td>
<td>0.7771</td>
<td>0.7939</td>
</tr>
<tr>
<td>S. Plains</td>
<td>0.5017</td>
<td>0.8411</td>
<td>0.7819</td>
<td>0.6072</td>
<td>0.1874</td>
</tr>
<tr>
<td>N. Plains</td>
<td>0.5853</td>
<td>0.7970</td>
<td>0.7010</td>
<td>0.5585</td>
<td>0.7181</td>
</tr>
</tbody>
</table>

To evaluate the performance of the maxUH and UVV variables to adequately portray the seasonal cycle of HCW, a comparison to the observational report database is made. Severe weather reports are obtained from the Storm Prediction Center (SPC) severe weather database files from [http://www.spc.noaa.gov/wcm/](http://www.spc.noaa.gov/wcm/) and serve as the observational data in which to compare proxy occurrence, despite the known issues in interpreting trends from the reports. Reports are mapped to the GCM grid and smoothed with a Gaussian filter. The comparison is made for the number of seasonal days exceeding the threshold of each proxy with the seasonal days of any
Figure 3.3. Comparison of standardized anomalies of mean seasonal precipitation (1971-2000) between the downscaled WRF simulations (top) and GFDL-CM3 (bottom) for (a) DJF, (b) MAM, (c) JJA, and (d) SON.
Figure 3.4. Mean number of days per season (top) and standardized anomalies (bottom) with daily precipitation accumulation exceeding (a) 0.25 mm, (b) 10 mm, (c) 25 mm, and (d) 50 mm.
severe weather reports, where the use of days is used to partially mitigate the known issues within the dataset. The mean seasonal observed and simulated severe weather days (days with maxUH ≥ 50 m²s⁻² and UVV ≥ 20 m s⁻¹) are compared in Figure 3.5. From this comparison, it is shown by means of pattern correlation of the standardized anomalies that both variables are moderately to strongly correlated with the observed severe days considering the entire CONUS, particularly so during the March–May months, though UVV has stronger correlation values for all four seasons as compared to maxUH. However, maxUH correlation during JJA is slightly misleading, as it does quite well when accounting for HCW days in the southern and northern Plains, with values of 0.751 and 0.877, respectively. However, maxUH is unable to account for severe days in the southeast and eastern U.S., similar to the results of Robinson et al. (2013). UVV days (defined using the 20 m s⁻¹ threshold ) are better able to capture activity in these areas, though they have a considerable high bias during MAM and JJA. Using a lower UVV threshold within the proxy tends to increase the coverage and frequency of occurrence, particularly in the western Gulf coast regions in MAM and the entire central U.S. during JJA, while also depicting new areas of severe occurrence, particularly in the eastern U.S. Increasing the threshold in MAM and JJA for UVV reduces the high bias in the central and southern U.S., but suffers from poorer performance in the eastern U.S. and during the winter and fall seasons. For this reason, and despite the higher bias in the previously discussed areas, the 20 m s⁻¹ threshold was chosen as an additional proxy to estimate a modeled severe occurrence. It appears that there may be a distinct seasonal and perhaps even regional variation in threshold in order to obtain a reasonable match with observed HCW days deduced from the report database, especially due to the fact that thresholds were chosen based upon the probability distribution function. While both proxies have their limitations, especially regionally, both reasonably replicate the observed annual cycle in severe weather activity.

The seasonal progression of tornado days is surprisingly well captured by the AFWAtor parameter (Figure 3.6. Using a threshold of 30 m s⁻¹ (roughly equivalent
to minimum EF-0 wind speed), the spatial correlation between standardized anomalies is strong for all four season, and is the strongest when compared to 40 and 50 $ms^{-1}$ thresholds. Nonetheless, the parameter does have a high bias the number of days during MAM and JJA, which is reduced using higher thresholds (RMSE is minimized using the maximum threshold value of 50 $ms^{-1}$). When considering maxGRPL and AFWAhail days, the mean seasonal cycle of severe hail days ($\geq 0.75$ inch; 1971–2000) is well captured, with very high spatial correlation values (Table 3.7), though the lower threshold of 25 $kgm^{-2}$ and mm tends to over-predict the magnitude of seasonal occurrences during MAM and JJA relative to the observational record (Figure fig:spchail). Increasing the threshold to 35 (mm/$kgm^{-2}$) for both AFWAhail and maxGRPL reduces the high bias, but at the expense of the degree of correlation, especially during DJF and SON. To be consistent with the reasoning used in choice of UVV threshold, the high bias will be excused in favor of a stronger spatial pattern of occurrence, especially in the cool season.

Little to no correlation is evident between the spatial patterns of modeled and observed seasonal days with severe convective winds in the cool season, and the spatial pattern is poorly captured in the spring. In the central Plains during the summer, the days with severe winds is marginally simulated, but strongly diverges from the pattern in the eastern U.S. evident from report days. The modeled annual frequency of days with maxWIND $\geq 20$ $ms^{-1}$ (Figure 3.8(b)) actually resembles more closely the severe convective wind gust climatology produced by observations from Automated Surface Observing System (ASOS) and Automated Weather Observing System (AWOS) sites, as illustrated in Figure 6(b) from Smith et al. (2013). This work had noted a significant deviation between the spatial patterns of reported severe winds (most of which were estimates) and those observed by ASOS/AWOS observing platforms. Despite the poor performance of this variable in replicating observed severe wind report days, it will still be investigated in order to gauge a potential response under future climate change.
Figure 3.5. Seasonal comparison of HCW days between the (a)–(d) SPC report database, (e)–(h) days with \( \text{maxUH} \geq 50 \text{ m}^2\text{s}^{-2} \), and (g)–(j) days with \( \text{UVV} \geq 20 \text{ ms}^{-1} \).
Figure 3.6. Comparison of seasonal mean severe hail days between the (a)–(d) SPC report database, (e)–(h) days with $\text{AFWAtor} \geq 30 \text{ ms}^{-1}$.
Figure 3.7. Comparison of seasonal mean tornado days between the (a)–(d) SPC report database, (e)–(h) days with $\text{AFW}_{\text{A}} \geq 30 \text{ m} \cdot \text{s}^{-1}$.
Figure 3.8. Comparison of annual mean days with (a) observed severe convective wind gusts and (h) days with maxWIND ≥20 ms⁻¹.
Table 3.6
Pearson correlation coefficient values and root mean squared error (RMSE) between mean seasonal maxUH and UVV days as compared to observed severe weather days (1971–2000).

<table>
<thead>
<tr>
<th>Season</th>
<th>Variable</th>
<th>Correlation</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>DJF</td>
<td>maxUH</td>
<td>0.774872</td>
<td>0.153492</td>
</tr>
<tr>
<td></td>
<td>UVV</td>
<td>0.809326</td>
<td>0.124935</td>
</tr>
<tr>
<td>MAM</td>
<td>maxUH</td>
<td>0.908205</td>
<td>0.444553</td>
</tr>
<tr>
<td></td>
<td>UVV</td>
<td>0.947117</td>
<td>1.438374</td>
</tr>
<tr>
<td>JJA</td>
<td>maxUH</td>
<td>0.565968</td>
<td>1.529109</td>
</tr>
<tr>
<td></td>
<td>UVV</td>
<td>0.808986</td>
<td>4.333098</td>
</tr>
<tr>
<td>SON</td>
<td>maxUH</td>
<td>0.56258</td>
<td>0.275955</td>
</tr>
<tr>
<td></td>
<td>UVV</td>
<td>0.803662</td>
<td>0.243416</td>
</tr>
</tbody>
</table>
Table 3.7
Pearson correlation coefficient values and root mean squared error (RMSE) for mean seasonal AFWAtor, AFWAhail, maxGRPL, and maxWIND days as compared to observed severe weather days by hazard type (1971–2000).

<table>
<thead>
<tr>
<th>Season</th>
<th>Variable</th>
<th>Correlation</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>DJF</td>
<td>AFWAtor</td>
<td>0.929621</td>
<td>0.018155</td>
</tr>
<tr>
<td></td>
<td>AFWAhail</td>
<td>0.811918</td>
<td>0.093146</td>
</tr>
<tr>
<td></td>
<td>maxGRPL</td>
<td>0.570797</td>
<td>0.057534</td>
</tr>
<tr>
<td></td>
<td>maxWIND</td>
<td>-0.07689</td>
<td>0.275479</td>
</tr>
<tr>
<td>MAM</td>
<td>AFWAtor</td>
<td>0.919541</td>
<td>0.52825</td>
</tr>
<tr>
<td></td>
<td>AFWAhail</td>
<td>0.957843</td>
<td>1.797716</td>
</tr>
<tr>
<td></td>
<td>maxGRPL</td>
<td>0.928755</td>
<td>0.650562</td>
</tr>
<tr>
<td></td>
<td>maxWIND</td>
<td>0.450475</td>
<td>0.538827</td>
</tr>
<tr>
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<td>AFWAtor</td>
<td>0.764977</td>
<td>0.722021</td>
</tr>
<tr>
<td></td>
<td>AFWAhail</td>
<td>0.838615</td>
<td>3.800406</td>
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<td></td>
<td>maxGRPL</td>
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<td>maxWIND</td>
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<td>1.166963</td>
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<td>AFWAtor</td>
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</tr>
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<td>AFWAhail</td>
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<td>0.221549</td>
</tr>
<tr>
<td></td>
<td>maxGRPL</td>
<td>0.700848</td>
<td>0.150824</td>
</tr>
<tr>
<td></td>
<td>maxWIND</td>
<td>-0.25246</td>
<td>0.286824</td>
</tr>
</tbody>
</table>
3.3.2 HCW Activity

A first glimpse into potential changes on proxy variables is visualized through distributions of non-zero values for the historical and future periods. The results maxUH and UVV are shown in Figures 3.9(a) and 3.9(b), respectively. In addition to these variables, the distribution of column-maximum simulated radar reflectivity factor (REFC) is also shown, as a means for gauging the distribution changes in overall convective activity. As illustrated, the future distribution of values for maxUH, UVV, and REFC all point to increased frequency of values, and in particular, for REFC and UVV, the largest relative increases occur at the higher intensity portion of the spectrum. Thus, not only does this suggest more frequent occurrence of convective storms, but also a greater number of more intense storms.

![Figure 3.9](image-url)

Figure 3.9. Smoothed distributions (based on histograms) for (a) maxUH, (b) UVV, and (c) REFC.

Mean Annual Changes

As a first approach to addressing potential changes in the convective climatology under a future climate, the mean annual threat will be examined. To address the overall question of convective storminess, the annual number of days with REFC > 50 dbZ has been compiled, as shown in Figure 3.10(a,d,g), which indicates that both the
historical and future simulations depict the greatest concentration of annual activity occurring in the southeastern U.S. An overall statistically significant increase in days with strong convective storms results within the future simulation period across the majority of the continental U.S. (a mean increase of over 9 days), with the exception of reduction in the number of days evident across the lower Florida peninsula and southern Texas. The greatest increase in the number of days is evident in the lee of the Rocky Mountains, a region known for frequent thunderstorm initiation (Lock and Houston, 2015). As for annual maxUH and UVV days ((b),(e),(h) and (e),(f),(i) of Figures3.10, respectively), both parameters highlight the similar areas of largest future increase in the northern Plains and southeastern U.S. Results herein associated with REFC are similar to those found by Gensini and Mote (2015). Of noticeable difference, however, is the magnitude of increase implied by each variable. By far, UVV day occurrences exceed that of maxUH for both current and future periods, and the degree of coverage is more localized for rotating storms (maxUH), as future changes in UVV proxy days encompass a larger portion of the CONUS.
Figure 3.10. Mean annual number of days with REFC $\geq 50\ dBZ$, maxUH $\geq 50\ m^2s^{-2}$, and UVV $\geq 20\ ms^{-1}$ for the (a)–(c) historical period (1971–2000) and (d)–(f) future period (2071–2100). The difference between the future and historical means are presented in (g)–(i), and stippling indicates where the distributions of annual means are statistically significant at the 95% confidence level.

Seasonal Cycle

To examine potential changes throughout the year, impacts upon changes in seasonal occurrence of strong convection and HCW proxy variables will be assessed. As noted previously, in addition to looking at the change in occurrence days, changes in the RCM grid point frequency of the variables will be illustrated, which may lend further insight into overall activity and areal coverage.

Similar to HCW environment changes, the largest relative increases in REFC, maxUH, and UVV occur during DJF compared to all seasons, with the Southeast region undergoing the greatest magnitude of change (Figures 3.11(i), 3.13(i), and 3.15(i), respectively). Similar increases in the normalized occurrence frequency are also seen
in this locale across these three variables (Figures 3.12(i), 3.14(i), and 3.16(i)). Further, a fairly strong uptick in convective activity is also indicated on the west coast in future climate.

During the spring months, the greatest increase in days and frequency of ≥50 dBZ events are noted for a large proportion of the country east of the Continental Divide (Figure 3.11(j)). The pattern of change for UVV strongly mimics that indicated by REFC, though the magnitude of projected change is slightly less (Figure 3.15(j)). The greatest increase in daily frequency during MAM for each of the REFC, UVV, and maxUH variables is concentrated along the corridor extending east from Missouri into the Ohio River Valley, a consequence of the north and eastward expansion of the seasonal threat area. Not only does the threat expand, but the general consensus suggests that the area of maximum activity also shifts to the northeast, from north central Texas to northeast Texas/southeast Oklahoma, similar to that seen in UVV. The frequency changes, on the other hand, undergo a maximum increase that is displaced further south and west from the areas of greatest seasonal increase in days, with results showing that UVV frequency nearly doubles in the area from northeast Texas into Missouri. This result is interpreted to mean that the largest increase in HCW days does not necessarily translate into more frequent and/or widespread increases in HCW occurrence.

Some of the greatest absolute increases in HCW activity occur during the summertime, where the number of days and occurrence frequency for REFC (Figure 3.11(k)), maxUH(Figure 3.13(k)), and UVV (Figure 3.15(k)) all undergo statistically significant rises in the northern Plains. A strong increase of greater than 10 REFC days are noted from along the front range of the Rocky Mountains from eastern Colorado northward into Montana, a result that is also seen in the increased number of days with strong updraft occurrences. Similar to the results in MAM, the greatest change in seasonal activity in terms of days does not align with the most notable rise in grid point frequency for both REFC and UVV, such that the most increases are displaced further east over the Dakotas and north central Nebraska (Figures 3.12(k))
and 3.16(k)). The latter may be indicative of a greater frequency in overnight MCS activity tied to the nocturnal low-level jet. Unlike the results of UVV and REFC, the shift in location between maximum increases in maxUH days and frequency is less drastic in this area. Elsewhere, all three variable indicate that the southern Plains undergoes a statistically significant decrease in the number of days meeting their respective thresholds, with maxUH days decreasing the most with a 30% reduction. These decreases extend into the lower Midwest for maxUH and REFC, though UVV remains relatively unchanged in the same areas. It is demonstrated, however, that while the number of REFC and UVV days decrease in the south central portions of the U.S., there is little to no change in the seasonal normalized frequency in those same areas. This is suggestive that under future climate, perhaps there may be fewer days with convection in these areas during the summertime, but the mean occurrence frequency changes little such that days that do experience storms may produce greater activity and/or areal coverage. Further, when considering days with higher thresholds of REFC and UVV (e.g., 60 dBZ and 30, 35, and 40 $ms^{-1}$ for REFC and UVV accordingly), only increases are seen during the season (See Figures B.3(k) and B.2(b),(d),(f) in Appendix B). On the other hand, the frequency of maxUH decreases in the same areas where the daily occurrence also lessens, such that the storms that are occurring within the model are less likely to acquire rotation, though areas in the northern Plains are more likely to see days with stronger rotational characteristics (Figure B.1). In the eastern U.S., activity indicated by REFC and UVV days on the east coast occurs, where REFC days undergo a drastic decrease (3–5 days) while UVV days actually rise by 3–4 days. Unlike maxUH, an increase in frequency in both days and grid point activation are noted in the eastern U.S. This seems to validate the motivation of using a different proxy for HCW rather than updraft helicity; strong convective events may be missed due to the requirement of a rotating storm. Overall, the areas with greatest HCW activity as indicated by UVV and maxUH follows the northwestward shift in HCW environments described in Chapter 2.
Turning to the autumn season, a general increase in the number of days with strong convective storms is evident from the desert southwest to the northeast and northward, with the strongest uptick in frequency encompassing much of the eastern U.S. For UVV, many areas in the eastern U.S. experience an increase of 1–2 days by the end of the century, with similar areas noting increased frequency, yet the increase in general is less than 5% in grid point frequency. The tendency for rotating storms (maxUH) suggests relatively weak (<0.5 day), though statistically significant, increases during the SON in the northern Plains and upper Midwest. Very similar areas are depicted as undergoing an increase in normalized frequency.

In terms of the diurnal distribution of HCW, the March through August period remains strongly diurnally forced, with maximum occurrences centering around the 2300–0000Z hours. In JJA, increases in maxUH occurrences largely occur after 0200Z, while UVV shows increases in frequency for all hours, though the largest increases do occur during the overnight hours. This activity could be strongly tied to an increase in MCS activity in the Northern Plains, as alluded to earlier. Overall, there is no compelling signal for a shift in peak activity according to time of day.
Figure 3.11. Seasonal mean days with REFC $\geq$ 50 dBZ days for the (a)–(d) 1971–2000 period, (e)–(h) 2071–2100 period, and (i)–(l) the difference between the means of the two periods. From left to right, the columns represent seasons DJF through SON.
Figure 3.12. Seasonal mean normalized grid point frequency of REFC ≥ 50 dBZ occurrences for the (a)–(d) 1971–2000 period, (e)–(h) 2071–2100 period, and (i)–(l) the difference between the means of the two periods. From left to right, the columns represent seasons DJF through SON. Stippling indicates where the distribution of seasonal means between the two periods are statistically significant at the 95% confidence level.
Figure 3.13. As in Figure 3.11, except for days with maxUH ≥ 50 m s^{-2}.
Figure 3.14. As in Figure 3.12, except for occurrences of maxUH ≥50 m s⁻². 
Figure 3.15. As in Figure 3.11, except for days with UVV $\geq 20$ ms$^{-1}$. 
Figure 3.16. As in Figure 3.12, except for occurrences of UVV $\geq 20\, ms^{-1}$. 
Figure 3.17. Mean diurnal distribution of maxUH (a)–(d) and UVV (e)–(h) by season for the historical (blue bars) and future (red bars) periods. Error bars indicate the 95% confidence interval estimated through a bootstrapping procedure.
Julian Date Analysis

As with HCW environments in the previous chapter, the probability by Julian date was computed for each of the HCW proxies for the historical and future 30-year periods (Figure 3.18). In addition to the minimum thresholds, stronger thresholds of 100 \( m^2 s^{-2} \) for maxUH and 30 \( ms^{-1} \) for UVV are also displayed to demonstrate that the probability of experiencing days with more intense values of updraft helicity and vertical velocity values will be experienced more often in the U.S. The overall aligns with environmental results in the Chapter 2, supporting the notion that the greatest increases in probability come in the tails of the annual distribution, that is, a greater probability of experiencing an HCW day both earlier and later in the calendar year. Regionally, peak probability for all regions has shifted earlier (Figures B.4 and B.5 and Table 3.8), with the most noticeable shifts evident for the Midwest and Northeast such that the peak has shifted from late to early summer. The greatest probability increases for maxUH occur earlier in the year, with all regions except for northern Plains experiencing decreased probability of occurrence after the peak relative to the historical climatology, generally within the May–September time frame. The reduced probability after peak timing is noticeably absent when considering the occurrence of UVV days, with the exception of a small decrease in the Southeast and southern Plains in July and August. Overall, the likelihood of a UVV proxy day for all regions increases, with the greatest gains occurring in the Southeast early and late in the calendar year (December–April) and in the Northeast from spring into early summer, with daily probabilities jumping by nearly 15%.

A consistent response in the number of accumulated HCW days suggests that a shift toward higher frequencies in the late 21st century climate is projected. In terms of raw frequencies, the mean signal also trends toward greater occurrences, though a much larger variation in the annual summation of grid point frequency is evident (Figures 3.19(b) and 3.20(b)), such that the mean annual summation of grid point frequency amasses a 38% (56%) and 101%(120%) increase in standard devia-
(a) maxUH $\geq 50 \text{ m}^2\text{s}^{-2}$  
(b) UVV $\geq 20 \text{ m}s^{-1}$  
(c) maxUH $\geq 100 \text{ m}^2\text{s}^{-2}$  
(d) UVV $\geq 30 \text{ m}s^{-1}$

Figure 3.18. 30-year mean probability of experiencing (a) maxUH $\geq 50 \text{ m}^2\text{s}^{-2}$, (b) UVV $\geq 20 \text{ m}s^{-1}$, (c) maxUH $\geq 100 \text{ m}^2\text{s}^{-2}$, and (d) UVV $\geq 30 \text{ m}s^{-1}$ anywhere in the CONUS (east of -105°W, land points only) by Julian day. The raw probabilities are represented by the scatter points, and a Gaussian filter is applied with $\sigma=15$ days, as in Brooks et al. (2003a), represented by the bold lines. The historical (1971–2000) and future (2071–2100) periods are represented by the navy and red lines, respectively.

tion (mean) for annual maxUH and UVV grid point frequency, respectively. Using the same methodology as used in the previous chapter, the empirical CDF for accumulated days (Figures 3.19(c) and 3.20(c)) and grid point frequencies (Figures 3.19(d)
Table 3.8
Change (in days) of the Gaussian smoothed peak probability of experiencing a maxUH and UVV day.

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<thead>
<tr>
<th></th>
<th>maxUH</th>
<th>UVV</th>
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<td>N. Plains</td>
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</table>

and 3.20(d)) for maxUH and UVV, respectively. Results illustrate the mean tendency for HCW proxy days and grid point frequencies to occur earlier in the annual cycle relative to the historical baseline. The change in days and frequency for both variables at different percentiles are given in Table 3.9. An interesting conclusion drawn from these numbers suggests that both variables indicate a lengthening of the overall season based upon HCW proxy days, with UVV much more pronounced. The majority of the accumulated frequency, however, shows that that bulk of activity in terms of grid point activation arises earlier relative to late 20th century simulated climate, with the maxUH signal being much more aggressive in this notion. Overall, these results support the previous findings of Gensini and Mote (2015) which suggested that HCW activity may occur earlier in the year under future 21st century climate.

To further investigate the potential for increased interannual variability of grid point frequency throughout the year, the daily total summation of grid point counts in the historical and future are examined (Figure 3.3.2). Results indicate that the mean frequency for maxUH increases, primarily in the December–June months, however, there is much stronger variability as evidenced by the fact that for several months,
Figure 3.19. Accumulated frequency of (a) maxUH days, (b) maxUH grid point frequency, and the empirical CDF of (c) maxUH days, (d) maxUH grid point frequency. Each individual year is plotted (historical in blue and future in red) with the means for the historical and future period represented by the solid and dashed black line, respectively.

The future holds some of the highest and lowest frequencies relative to the historical baseline. The mean frequency of UVV increases for all calendar months, though the most notables times are between March and October. Again, the interannual variability is quite large, and the range of values extends a much larger spectrum of values. This greater variability is evident across all regions for both variables.
(a) Accumulated UVV days  
(b) Accumulated UVV frequency  
(c) Empirical CDF of UVV days  
(d) Empirical CDF of UVV frequency

Figure 3.20. As in 3.19, except for UVV $\geq 20 \text{ ms}^{-1}$.

(Figures B.6 and B.7). There is a tendency for maxUH frequency to incur the largest regional increases between March and June, with the peak time of mean maximum frequency shifting from July to May. In the Southeast, the variability in period between December and April appears much more variable, especially in terms of maxUH occurrence. The timing in peak activity remains generally consistent in the southern and northern Plains areas, both for maxUH and UVV.
Table 3.9
Mean differences in days for several percentiles of the empirical CDFs for maxUH and UVV days and grid point frequencies.

<table>
<thead>
<tr>
<th>Percentile</th>
<th>Days</th>
<th>Frequency</th>
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</tr>
</tbody>
</table>
Figure 3.21. Daily grid point frequency of (a) maxUH $\geq 50\ m^2\ s^{-2}$ and (b) UVV $\geq 20\ ms^{-1}$ for each year of the historical (blue lines) and future (red lines) periods. Raw data have been smoothed with a Gaussian filter ($\sigma=15$ days) The mean daily frequency values for the historical (future) period are represented by the solid (dashed) black lines.
3.3.3 Insight into Hazard Type

Distribution Changes

This section will explore the changes in storm-scale parameters that may be related to specific HCW type (i.e., tornado, wind, and hail). In particular, the AFWAtor, AFWAhail, maxGRPL, and maxWIND proxies will be interrogated for potential changes in future climate. To begin, the smoothed distributions based on histograms with bin size of 1 unit is displayed for each variable in Figure 3.3.3. Demonstrated is an increased in grid point frequency in the future for all variables. For both AFWAtor and maxGRPL, the strongest rises in frequency materialize at higher values. Increases in AFWAhail frequency generally ensue after about 15 mm, while the future and historical distributions of hourly maximum wind speed tend not to diverge until more extreme values are reached. These results lend support to the notion that not only could the occurrence of each hazard type become more frequent, but also more intense.
Figure 3.22. Smoothed distributions (based on histograms) depicting the distribution of values for (a) AFWAtor, (b) AFWAhail, (c) maxGRPL, and (d) maxWIND. The historical period is shown in blue and the future in red.

Mean Annual Changes

As in previous results, the first glimpse into the spatial patterns of projected changes are demonstrated based upon mean annual frequency of days exceeding the respective minimum threshold for each parameter. Based on these results (Figure 3.23), it is readily apparent that each parameter has been modulated by projected changes in environmental conditions, resulting in statistically significant increases
in yearly frequency. Because of the dependence on updraft helicity, it comes as no surprise that the spatial patterns of change for AFWAtor and AFWAhail emulate that of maxUH days (previously shown Figure 3.10(h)). Increases in AFWAtor day on the order of 1–2 days per year are noted in the southeastern U.S. and the northern Plains, with greater increases in hail potential of 3–5 days in those same areas. Both maxGRPL and maxWIND suggest statistically significant increases across most of the United States, with the primary focus in the eastern two-thirds of the CONUS where frequency rises nearly 85% and 150% above the historical annual mean, respectively. In general, both AFWAhail and maxGRPL feature the central corridor of the country as the most prominent location for hail frequency, though the magnitude and spatial distribution of projected frequency are markedly different, with maxGRPL advocating for more aggressive rises in daily occurrence. The latter variable does not take into account any environmental information as AFWAhail does, therefore the variation is understandably distinct.
Figure 3.23. Mean annual number of days with (a) AFWAtor ≥ 30 ms⁻¹, (b) AFWAhail ≥ 25 mm, (c) maximum column integrated graupel ≥25 kg m⁻², and (d) hourly maximum 10 m wind speed ≥20 ms⁻¹ (in the presence of at least 40 dBZ reflectivity values at 1 km AGL).
Seasonal Cycle

In terms of potentially tornadic days, results indicate enhanced recurrence of days with AFWAtor values exceeding 30 ms$^{-1}$ in the future (Figure 3.24). Confined to the southeast during DJF, the increases amount to an average of $\sim$1 additional day of occurrence ($\sim$450% increase), while nearly the entire eastern two-thirds of the United States realizes heightened frequency during the months of March, April, and May, demonstrating a nearly 140% inflation in potentially tornadic days. Throughout JJA, as in maxUH, a reduction in days is evident from the southern Plains states northeast into the Midwest. This represents a decline of 15–25%, nevertheless there is a persistent signal in the northern Plains of greater activity. The enhancement of more frequent daily incidences of AFWAtor days with higher thresholds is supported during DJF, MAM, and JJA (see Figure B.9), which lends further support that these seasons could become more favorable for tornadoes in the future.

The representation of seasonal hail frequency by the AFWAhail and maxGRPL proxies are revealed in Figures 3.25 and 3.26. Each parameter indicates statistically significant increases across all four seasons. There is an overall agreement in placement and magnitude in the Southeast during DJF, amounting to just over 1 additional day with severe hail during the season. Results are spatially consistent during the springtime, with each parameter indicating a future expansion further north and east of the projected seasonal days of occurrence, though the maximum frequency remains over the southern Plains, and western portions of the Southeast region. The magnitude of increase projected is only slightly different, on average a deviation of about 1 day, such that the potential exists for 2–3 more days with severe hail per season over the CONUS east of the Continental Divide. A divergence in the projected hail response is evident during the summer, with AFWAhail noting reductions in the Southeast, southern Plains and Midwest regions due to the decreased frequency of rotating storms in those regions. However, the message of increase overlaps in the areas from eastern Colorado northward into the northern Plains and upper Midwest,
with an average increase of over 2–3 days in northern Plains region during JJA. East of the Mississippi River Valley, maxGRPL paints a picture of changing hail days that is closely aligned with the projected days with stronger updraft frequency (UVV $\geq 20 \text{ ms}^{-1}$; Figure 3.15(k)). During the fall, relatively weaker, though still significant, increases on the order of 0.5 days per season with the AFWAhail parameter suggesting rises in the upper Midwest while maxGRPL increases encompass a larger area from the southwestern U.S. northeastward through the Midwest and extending into the New England area. Altogether, AFWAhail closely follows the pattern of maxUH while maxGRPL follows the general pattern of the UVV proxy, such that the hail occurrence depicted by AFWAhail is directly tied to the presence of storm rotation. The prevailing signal from each proxy is for the most notable increases to occur during MAM and JJA, with a tendency for a potential increase in days with larger hail size as well, evidenced by statistically significant increases in the number of days where AFWAhail and maxGRPL exceed increasingly higher thresholds (Figures B.10 and B.11).

Lastly, the potential changes in convective wind threat (in which the lowest confidence in representation has been instilled), are presented in Figure 3.27. In the future, the maxWIND proxy still does not capture occurrence of severe wind events along the Gulf Coast states, and the slight increase seen in those areas and along the Atlantic coast are not statistically significant. Instead, the main area of activity in convectively driven wind climatology lies over east central California, in the lee of the Sierra Nevada, a location known for high wind events (e.g., Zhong et al., 2008). An appreciable signal in enhanced events are displayed in MAM and JJA, which is much more aligned with overall picture painted by other severe proxies, such that more confidence can be placed that maxWIND may be able to detect severe wind occurrences during the seasons in which they are most often observed. Springtime wind events still highlight the central corridor of the U.S. and into the Midwest as the locations with greatest seasonal frequency, and the uptick in frequency occurs within these same areas, assembling an average increase of greater than 1 day per
season in the future. The greatest response is garnered during JJA in the northern
Plains states, with an average rise of nearly 4.5 days of severe wind events, though
the entire eastern portion of the U.S. predicts a nearly 300% increase. Similar to the
results painted by maxGRPL and UVV during the autumn, the potential increases
in convective wind gust events are advertised from areas extending from the desert
Southwest northeastward into the upper Midwest. Though weaker in absolute in-
creases (∼0.25–0.5 days/season), the growth amounts to a relative increase on par
with that of JJA, on the order of 300%.
Figure 3.24. As in Figure 3.11, except for occurrences of AFWAtor $\geq 30$ m s$^{-1}$. 

[Map images showing data distribution across different regions with color scales indicating occurrences of AFWAtor]
Figure 3.25. As in Figure 3.11, except for occurrence of AFWA hail $\geq 25$ mm.
Figure 3.26. As in Figure 3.11, except for occurrences of maxGRPL $\geq 25 \text{ kgm}^{-2}$.
Figure 3.27. As in Figure 3.11, except for occurrences of maxWIND $\geq 20$ m s$^{-1}$. 
Julian Date Analysis

Just as in previous results, the probability by Julian date was computed for each of the AFWAtor, AFWAhail, maxGRPL, and maxWIND proxy variables for the historical and future 30-year periods. The AFWAtor and AFWAhail parameters illustrate very similar annual probability curves and for both the historical and future periods, which associate closely with the probability curves of maxUH (refer to Figure 3.18(c)). The overall pattern for each of these variables is suggestive of the greatest increases in occurrence day probability arising during the early months of the year in addition to the late fall/early winter time. Further, it is visually indicated that the HCW season may become lengthened by the general widening of the distribution (though less so for AFWAtor and AFWAhail). Comparatively, the probabilities using higher thresholds are illustrated in Figure 3.29; an unmistakable rise in probability of experiencing days with larger hail and stronger winds in the future relative to the 1971–2000 time period, especially during the May–October time frame. Peak probability increases for maxGRPL ≥50 $kgm^{-2}$ and maxWIND ≥30 $ms^{-1}$ amount to around a 40% increase each, and occur in late July and early August. Enhanced probability of experiencing a day with AFWAtor ≥50 $ms^{-1}$ is shifted upward nearly 10% from the beginning of the year to early summer.

Using the same procedure used with maxUH and UVV, the empirical CDF is derived to detect where days of occurrence are being accumulated. From these results (listed in Table 3.9 and visualized in Figure 3.30), previous conclusions of a lengthened HCW season based upon days of hazard occurrence is supported. For example, considering the period of time between the 20th and 80th percentiles (i.e., where 60% of the total annual days are accumulated), this duration of time is on average extended by 16, 23, 16 and 8 days for AFWAtor, AFWAhail, maxGRPL, and maxWIND, respectively. Interpretation of the accumulated frequency CDF (Figure 3.33), offers a departure in interpretation based upon accumulated days, with trends in AFWAtor, AFWAhail, and maxGRPL frequency more suggestive that the bulk of future occur-
rences will occur earlier than in the past. On the other hand, while maxWIND days are aggregated earlier, the tendency for a slower accumulation in frequency during the first half of the year is implied by these results.

Analysis of the interannual variability of these proxies will conclude the discussion on hazard type. Both the mean accumulated days and frequency undergo striking rises (Figures 3.31 and 3.32), but evident is a greater increase in the variation. As with maxUH and UVV, there is a clear shift toward greater annual grid point frequencies for each parameter with a corresponding increase in the variability compared to results from 1971–2000 climatology (see Figure 3.32). Accordingly, the increase in standard deviation for annual frequency sum is on the order of 45%, 59%, 156%, and 189% for AFWAtor, AFWAhail, maxGRPL, and maxWIND, correspondingly. A visualization of the mean frequency and its variability throughout the annual cycle are shown in Figure 3.34. In the same manner that the probability plots shown in Figure 3.28 demonstrate the annual cycle of occurrence day probabilities, these figures demonstrate the frequency cycle, which tends to follow a similar pattern in timing and distribution shape. Gleaned from these results, the AFWAtor parameters appears to be the most variable from year-to-year, though each proxy displays a broader range of daily frequencies in the future. In terms of the peak timing of frequency, this historical and future periods more or less resemble each other, though there is an indication that maxGRPL frequencies have shifted earlier, from mid-July to mid-May.
(a) $\text{AFWA}_{\text{tor}} \geq 30 \text{ ms}^{-1}$

(b) $\text{AFWA}_{\text{hail}} \geq 25 \text{ mm}$

(c) $\text{maxGRPL} \geq 25 \text{ kgm}^{-2}$

(d) $\text{maxWIND} \geq 20 \text{ ms}^{-1}$

Figure 3.28. 30-year mean probability of experiencing (a) $\text{AFWA}_{\text{tor}} \geq 30 \text{ ms}^{-1}$, (b) $\geq 25 \text{ mm}$, (c) $\text{maxGRPL} \geq 25 \text{ kgm}^{-2}$, (d) $\text{maxWIND} \geq 20 \text{ ms}^{-1}$ anywhere in the CONUS (east of -105°W, land points only) by Julian day. The raw probabilities are represented by the scatter points, and a Gaussian filter is applied with $\sigma = 15$ days, as in Brooks et al. (2003a), represented by the bold lines. The historical (1971–2000) and future (2071–2100) periods are represented by the navy and red lines, respectively.
Figure 3.29. 30-year mean probability of experiencing (a) AFWAtor ≥ 50 ms$^{-1}$, (b) ≥ 50 mm, (c) maxGRPL ≥ 50 kgm$^{-2}$, (d) maxWIND ≥ 30 ms$^{-1}$ anywhere in the CONUS (east of -105°W, land points only) by Julian day. The raw probabilities are represented by the scatter points, and a Gaussian filter is applied with σ = 15 days, as in Brooks et al. (2003a), represented by the bold lines. The historical (1971–2000) and future (2071–2100) periods are represented by the navy and red lines, respectively.
Figure 3.30. Empirical CDF of annual accumulated occurrence days for (a) AFWator $\geq 30 \text{ ms}^{-1}$, (b) $\geq 25 \text{ mm}$, (c) maxGRPL $\geq 25 \text{ kgm}^{-2}$, (d) maxWIND $\geq 20 \text{ ms}^{-1}$. Each individual year is plotted (historical in blue and future in red) with the means for the historical and future period represented by the solid and dashed black line, respectively.
(a) AFWAtor

(b) AFWAhail

(c) maxGRPL

(d) maxWIND

Figure 3.31. Annual accumulated occurrence days for (a) AFWAtor $\geq 30 \text{ ms}^{-1}$, (b) $\geq 25 \text{ mm}$, (c) maxGRPL $\geq 25 \text{ kglm}^{-2}$, (d) maxWIND $\geq 20 \text{ ms}^{-1}$. Each individual year is plotted (historical in blue and future in red) with the means for the historical and future period represented by the solid and dashed black line, respectively.
Figure 3.32. Annual accumulated frequency of grid point occurrences for (a) $AFWAtor \geq 30\, ms^{-1}$, (b) $\geq 25\, mm$, (c) $maxGRPL \geq 25\, kgm^{-2}$, (d) $maxWIND \geq 20\, ms^{-1}$. Each individual year is plotted (historical in blue and future in red) with the means for the historical and future period represented by the solid and dashed black line, respectively.
Figure 3.33. Empirical CDF of annual accumulated frequency of grid point occurrences for (a) AFWAtor $\geq 30 \text{ ms}^{-1}$, (b) $\geq 25$ mm, (c) maxGRPL $\geq 25 \text{ kgm}^{-2}$, (d) maxWIND $\geq 20 \text{ ms}^{-1}$. Each individual year is plotted (historical in blue and future in red) with the means for the historical and future period represented by the solid and dashed black line, respectively.
Figure 3.34. Daily grid point frequency of (a) AFWAtor \( \geq 30 \text{ ms}^{-1} \), (b) \( \geq 25 \text{ mm} \), (c) maxGRPL \( \geq 25 \text{ kgm}^{-2} \), (d) maxWIND \( \geq 20 \text{ ms}^{-1} \) for each year of the historical (blue lines) and future (red lines) periods. Raw data have been smoothed with a Gaussian filter (\( \sigma = 15 \text{ days} \)) The mean daily frequency values for the historical (future) period are represented by the solid (dashed) black lines.
Table 3.10
As in Table 3.9, except for AFWAtor, AFWAhail, maxGRPL, and maxWIND, respectively.

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3.4 Summary

Under the historical and future (RCP8.5) experiments from CMIP5, this work utilized projections from the GFDL-CM3 model to drive high-resolution (4-km) regional climate simulations using WRF. A daily re-initialization integration procedure was adopted in favor of the more traditional continuous integration procedure employed in regional climate modeling. To address the temporal limitations of previous work, both in terms of the number of years and length of simulated months, the entire annual cycle was simulated for two 30-year periods (1971–2000 and 2071–2100). The general characteristics of the historical WRF simulations were investigated to assess how well they were able to reasonably replicate current climate. It was shown that on average, the model had a cool, dry bias relative to observations, a characteristic likely inherited from the global climate model. The prevailing pattern in mean seasonal precipitation was relatively well represented during DJF, MAM, and SON. However, a notable divergence in precipitation climatology was found during JJA, where a persistent dry bias was identified in the southeastern portions of the country along the coastline of the Gulf of Mexico, likely related to sea-breeze induced convection. Despite this discovery, the coastal regions in the southeast and in Florida collected the greatest number of days during the season with measurable rainfall, from small to more significant accumulations, relative to the entire domain. In spite of the poor representation of seasonal rainfall accumulation in this region, it is unlikely that this deficiency would strongly affect the representation of the HCW climatology in this region.

Two storm-scale proxies were utilized to estimate the occurrence of HCW within the model simulations. Hourly maximum updraft helicity values (maxUH) were utilized as in previous work (e.g., Trapp et al., 2011; Robinson et al., 2013; Gensini and Mote, 2014, 2015) to detect the presence of rotating storms. As rotation is not a characteristic of all severe storms, it was hypothesized that the use of the use of hourly maximum updraft vertical velocity (UVV) may be more suitable for gauging storm
intensity for all modes of convection, and alleviate some of the summertime HCW underestimates evident in the far eastern U.S. as noted by Robinson et al. (2013), for example. An evaluation of the potentially severe days based on maxUH and UVV against the observed severe thunderstorm days from the historical records indicated that overall the seasonal cycle was well captured, though the choice of threshold resulted in an overestimation of occurrence days during MAM and JJA, a consequence accepted in favor of a greater spatial pattern correlation.

Overall, it was found that the influence of anthropogenic climate change upon severe storms likely will increase both their frequency and intensity. However, the interannual variability of occurrence was found to greatly increase under future climate, such that some change in the larger-scale environmental controls may be responsible for some of these patterns identified. Potential contributors to the variability may arise due to increases in CIN, decreased ETC frequency, or changes in atmospheric blocking patterns, as some research has suggested may occur. As in the analysis of favorable environments in the Chapter 2, it was found that on average, HCW events were occurring earlier in the annual cycle, likely due to the earlier increase in CAPE within the GCM projections. The early season HCW appearance had the largest relative increase among all seasons, highlighting the southeastern U.S. The mean occurrence day frequency during MAM underwent a 160% (maxUH) to 220% (UVV) increase, and the average risk area expanded further north and east relative to the historical climatology. A noticeable northward shift in the area with greatest seasonal HCW days was seen in JJA, with a fewer number of days with maxUH and UVV evident in the southern Plains in the future simulations. Interestingly, a corresponding decrease in the grid point frequency was not seen for UVV, which is perhaps an indication that there may be fewer days with strong updrafts of at least 20 $m s^{-1}$ in magnitude, but that the average seasonal frequency may stay within the normal realm, or slightly increase. It should be noted, however, that it is unclear whether the changes in frequency indicate more individual storms or just a larger areal coverage.
Lastly, in addition to maxUH and UVV, an attempt was made to use other output variables to estimate the occurrence of individual hazard types (tornado, wind, hail). Collectively, these results from experimentation with four different proxies to estimate different hazard type, indicate that tornadoes and hail may be the main hazards undergoing increase during the the cool season, however given the poor representation of the observed severe wind climatology, the risk for an enhanced wind threat during DJF cannot be ruled out. All hazards appear to be augmented in MAM and JJA results, with a general agreement that much of the CONUS east of the Rockies are at risk for additional days of all hazard types. Finally, during SON, hail and wind potential offer the greatest signal of potential hazard type change. From the hail proxies, there is an overwhelming signal suggestive of a greater occurrence of hail events, but also that larger hailstones may also be realized more often, particularly in the summertime when the largest increases in CAPE are projected. A similar strong increase in probability is seen for days with stronger convective wind gusts realized by the model. It is likely that these changes are driven by the significant CAPE increases evident within the GFDL-CM3 projection.

In summary, this chapter presented a methodology whereby simulations of future climate in the United States were performed using a convection-permitting regional climate model (WRF) with the purpose of investigating climate change impacts upon severe storms. To analyze such a response, outcomes from storm-scale characteristics were shown to offer a glimpse into potential changes in HCW in a warmer climate. Results herein have indicated the possibility for a discernible increase in both frequency and intensity of HCW events under an aggressive climate change scenario, with a subsequent rise in variability.
CHAPTER 4. COMPARING MODELING APPROACHES

4.1 Introduction

This section will compare results from the environmental ("implicit") modeling approach with that of high-resolution dynamical downscaling ("explicit") approach to the question of climate change and HCW. Due to the large computational expense incurred through dynamical downscaling, the question of what knowledge is gained over environmental approach by downscaling is posed. A noted limitation of the environmental approach is the assumption that the rate of storm initiation due to the presence of a favorable HCW environment remain constant. Neglecting any changes in forcing for convective initiation, by nature of the increased frequency in favorable HCW environments from GFDL-CM3, a corresponding rise in the occurrence of HCW should result. Indeed, results from high-resolution dynamically downscaled simulations indicate that severe storms are realized more often within these environments. Of interest, however, is the proportion of these environments that go on to produce storms and whether that relationship between the environment and HCW occurrence has changed. This topic has yet to be directly addressed by any regional climate modeling study investigating changes in severe storms.

4.2 Methods

To investigate, these questions will be approached in a two different ways. First, the spatial patterns of projected HCW environment and proxy occurrences will be compared, using the same approach of correlating standardized anomalies as used in the previous chapter when comparing seasonal precipitation. In this way, the pattern correlation can be determined to allow address the question of when and where each each of the two approaches depict HCW activity. Next, a simple linear regression
between the average monthly HCW environment days against HCW proxy days from the regional climate simulations will be performed, where means are computed for land points east of -105°W. In this manner, the linkage between the large-scale environment and the simulated HCW occurrences from the downscaled simulations is then investigated. Both of these procedures aim to help explain the degree to which larger-scale environmental controls account for changes in storm-scale attributes, and subsequently, the correspondence between implicit and explicit approaches to the research problem. Hence, insight into the utility of the more detailed and computationally expensive approach of dynamical downscaling may be gained.

4.3 Results

To start, an examination of the pattern correlation between the occurrence of maxUH and UVV days with several different HCW environmental parameters from the GFDL-CM3 RCP8.5 projection is explored. As an illustration, the standardized anomalies for mean $NDSEV_{sig}$ and maxUH days for JJA are illustrated in Figure 4.3 for both historical and future periods of interest. From a visual standpoint, this example shows that both the environmental control and resulting maxUH days during JJA each highlight that the most active days occur in the central and northern Plains into the upper Midwest. Further, both environment and event anomalies display a northwestward shift in maximum activity in the future. Indeed, high correlation values are achieved between $NDSEV_{sig}$ and maxUH during JJA, with values of 0.8950 and 0.9470 for the historical baseline and future projection, accordingly. Overall, the areas with the greatest frequency in favorable HCW environments are fairly well aligned with the areas of most frequent HCW days (maxUH and UVV) within the downscaled simulations (Table 4.1). Thus, not unexpectedly, the large-scale environment modulates the timing and locations of ensuing events, though the autumn season presents the weakest relationship, especially when considering $NDSEV_{1,6}$. 
Figure 4.1. Standardized anomalies of (a),(c) $NDSEV_{sig}$ days and (b),(d) days with maxUH ≥ 50 m$^2$s$^{-2}$. The top row represents results from the historical simulations, and the bottom row the future projections.

To better investigate the relationship between the environmental controls and simulated HCW events, a simple ordinary least-squares linear regression was performed for both climatological periods, relating monthly mean HCW environment days with monthly mean maxUH and UVV days (N=360 for each period). To illustrate, results demonstrating the association between $NDSEV_{sig}$ days and maxUH and UVV days are shown in Figures 4.2(a) and 4.2(b), which indicate that the relationships are linear with coefficient of determination ($R^2$) values ranging from 0.76 to 0.9. It should be noted that the plots of the linear fit have been extrapolated. It is readily apparent that the slope of each line differs, which has been shown to be statistically significant at the 95% confidence level through an analysis of covariance (ANOVA) procedure (see Table 4.2). The interpretation of such a response indicates that the
Table 4.1

Pearson correlation coefficients between the mean CONUS seasonal standardized anomalies of HCW days and days with maxUH $\geq 50 \text{ m/s}^2$ and days with UVV $\geq 20 \text{ m/s}$ for both the historical and future periods.

<table>
<thead>
<tr>
<th></th>
<th>DJF</th>
<th>MAM</th>
<th>JJA</th>
<th>SON</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>maxUH</td>
<td>UVV</td>
<td>maxUH</td>
<td>UVV</td>
</tr>
<tr>
<td>NDSEV$_{1.6}$</td>
<td>historical</td>
<td>0.7274</td>
<td>0.7090</td>
<td>0.9560</td>
</tr>
<tr>
<td></td>
<td>future</td>
<td>0.7726</td>
<td>0.7390</td>
<td>0.9320</td>
</tr>
<tr>
<td>NDSEV</td>
<td>historical</td>
<td>0.8563</td>
<td>0.8430</td>
<td>0.9720</td>
</tr>
<tr>
<td></td>
<td>future</td>
<td>0.8881</td>
<td>0.8540</td>
<td>0.9540</td>
</tr>
<tr>
<td>NDSEV$_{sig}$</td>
<td>historical</td>
<td>0.8880</td>
<td>0.8900</td>
<td>0.9120</td>
</tr>
<tr>
<td></td>
<td>future</td>
<td>0.9830</td>
<td>0.9590</td>
<td>0.9300</td>
</tr>
<tr>
<td>NDSEV$_{tor}$</td>
<td>historical</td>
<td>0.3607</td>
<td>0.2830</td>
<td>0.8200</td>
</tr>
<tr>
<td></td>
<td>future</td>
<td>0.7177</td>
<td>0.7980</td>
<td>0.8660</td>
</tr>
<tr>
<td>STP</td>
<td>historical</td>
<td>0.8624</td>
<td>0.8710</td>
<td>0.9520</td>
</tr>
<tr>
<td></td>
<td>future</td>
<td>0.9269</td>
<td>0.8790</td>
<td>0.9280</td>
</tr>
</tbody>
</table>

The future relationship between environment and event has been altered relative to that of the 1971–2000 relationship. In this case, there is a strong increase in the mean number of days with favorable environmental conditions, but the response of the environment (production of a simulated severe event) has been reduced. Regionally, very similar results are shown, though the West region has a poorer linear fit with generally less than 30% of the variability explained by the model (Figures C.3 and C.4). Additionally, other HCW environmental parameters, in particular NDSEV$_{1.6}$, NDSEV, and NDSEV$_{tor}$ indicate a strong linear relationship between environment and event days (see Table 4.2), which also note very similar modifications between the current and future climate (statistically significant differences in slope). STP represents an exception to these results; while STP presents itself as a fairly poor predictor of HCW events for the eastern CONUS, on a regional basis it is much more well correlated with maxUH days. In particular, a much stronger proportion of variance for the linear model is explained for the northern and southern Plains, the
Midwest, and the Southeast regions with corresponding $R^2$ values of 0.8536(0.8385), 0.6491(0.6955), 0.0.7355(0.7193), and 0.5744(0.7162) for the historical(future) time period, respectively.

Due to the reduction in seasonal UVV and maxUH days for certain regions during JJA, as noted in Chapter 3 (refer to Figures 3.13(k) 3.15(k)), it is hypothesized that the summertime may be having the strongest influence upon the changing linear relationship between the two climatological periods. Stratifying by season, it becomes readily apparent that a large departure between regression lines does occur during JJA (see Figures C.5 and C.6 in Appendix C. However, MAM and SON also display significantly different slopes for the historical and future regression lines for maxUH, though differences in slope for UVV days were only significant during MAM and JJA. Interestingly, both maxUH and UVV proxies illustrate relatively little difference during DJF, such that we fail to reject the null hypothesis that the two slopes are equal (p-value of 0.6949 and 0.7607 for maxUH and UVV, respectively). The subsequent test for a significant displacement in y-intercept revealed that the intercept locations differ only for UVV, an outcome that can be naively interpreted from the chart. Though the linear relationship is relatively weaker, this result then indicates that, though the slope does not differ, a greater mean number of UVV days occur relative to mean monthly $NDSEV_{sig}$ days.
Table 4.2
Slope, y-intercept, $R^2$, and ANCOVA p-values of the linear regression between environmental parameters and days with \( \text{maxUH} \geq 50 \, \text{m}^2\text{s}^{-2} \) and \( \text{UVV} \geq 20 \, \text{ms}^{-1} \).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Period</th>
<th>maxUH days</th>
<th>UVV days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>slope</td>
<td>y-intercept</td>
<td>$R^2$</td>
</tr>
<tr>
<td>$NDSEV_{1.6}$</td>
<td>historical</td>
<td>0.3055</td>
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<td></td>
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<td>0.227</td>
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<td>$NDSEV$</td>
<td>historical</td>
<td>0.2889</td>
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<td></td>
<td>future</td>
<td>0.1567</td>
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<tr>
<td>$NDSEV_{\text{sig}}$</td>
<td>historical</td>
<td>0.6229</td>
<td>-0.047</td>
</tr>
<tr>
<td></td>
<td>future</td>
<td>0.3419</td>
<td>-0.088</td>
</tr>
<tr>
<td>$NDSEV_{\text{tor}}$</td>
<td>historical</td>
<td>1.1867</td>
<td>0.0894</td>
</tr>
<tr>
<td></td>
<td>future</td>
<td>0.5754</td>
<td>0.0582</td>
</tr>
<tr>
<td>$STP$</td>
<td>historical</td>
<td>0.6108</td>
<td>0.1367</td>
</tr>
<tr>
<td></td>
<td>future</td>
<td>0.4684</td>
<td>0.1805</td>
</tr>
</tbody>
</table>
Figure 4.2. Linear regression between U.S. (east of -105°W; land points only) monthly mean $NDSEV_{sig}$ days and (a) days with $maxUH \geq 50 m^2 s^{-2}$ and (b) $UVV \geq 20 ms^{-1}$ days. Monthly mean HCW environment days for each of the 30-years of historical (1971–2000; navy line and scatter points) and future (2071–2100; maroon line and scatter points) periods serve as the predictors. Bootstrapped 95% confidence intervals are shaded.
4.4 Summary

As a whole, a strong correlation between HCW environment and proxy days has been demonstrated. Both the implicit and explicit approaches depict similar spatiotemporal patterns of projected HCW activity, albeit the storm-scale HCW proxy days occur at a much lesser frequency than HCW environment days. The strongest agreement in spatial patterns are predominantly seen in DJF, MAM, and JJA. Each approach reveals similar areas of enhanced future activity, such that HCW events are largely governed by the environmental conditions. This is an encouraging result in terms of the downscaling technique used. Despite the coarse resolution of the GCM and the choice of integration procedure, the regional climate simulations are able to maintain consistency between the GCM and RCM, particularly in terms of spatial patterns.

Through regression of monthly mean values, it becomes evident that increased HCW proxy days indeed arise from increased HCW environments, though the rate at which the environments result in a simulated HCW day is not consistent between the two epochs. As previous research has advised, the implicit approach of analyzing HCW environmental parameters suffers from the assumption that storms will be initiated, and at the same rate in the future no less. Consequently, these results solidify that this is certainly a limiting expectation, providing evidence that the occurrence of HCW environments alone are insufficient to infer projected modifications in HCW events. The unequal response of favorable environments between the two periods justifies the motivation for use of dynamical downscaling to investigate the environment-event relationship of severe storms in the context of climate change. Additionally, the outcome suggests that processes which aid in initiation of convection, whether on the synoptic and/or mesoscale, may have undergone change in a future climate. It is speculated that perhaps the increase in CIN analyzed in Chapter 2 may play a role in suppressing convection, while other changes in mid-latitude weather may also contribute. For the latter, these results may be tied to the projected change
in frequency of extratropical cyclones (ETCs) by the end of the 21st century. The analysis of ? demonstrated that the frequency of ETCs over the CONUS within the GFDL-CM3 simulations (2081–2100) decreases across all four seasons (-1.8%, -5.8%, -24.5%, and -16.3% for DJF, MAM, JJA, and SON, respectively), though results are only statistically significant for MAM, JJA, and SON. Qualitatively, the reduction in ETCs appear plausible in their connection to the results presented herein. However, at this time, a thorough investigation into the potential causative mechanism(s) responsible for these results has not been performed, and thus warrants further examination.
CHAPTER 5. SUMMARY AND CONCLUSIONS

Growing evidence from climate model projections suggest that large-scale environmental conditions favorable for severe thunderstorms will increase in response to elevated greenhouse forcing by the end of the 21st century. The implications of such an increase, combined with rising social vulnerability, could mean future losses due to severe storms may undergo an accelerated enhancement. This work aimed to explore the potential impacts anthropogenic climate change may have upon hazardous convective weather in the United States through two different methodologies: first, by analysis HCW-favorable environmental conditions projected by a GCM (GFDL-CM3), and secondly, through an use of a high-resolution non-hydrostatic mesoscale model to simulate regional climate. As a result, the latter method allows for an explicit treatment of deep convection such that the model to intrinsically develop the relationship between the large scale environment and the ensuing convective events, and thus account for convective initiation. The latter has limited the number of studies which have utilized this approach due to the computational expense, but with the advancement of computing resources in addition to the growing availability of GCM data on a sub-daily temporal frequency, it has now become more feasible. Henceforth, the linkage between the two separate approaches were investigated to provide additional insight into the impact of environment-event relationships in future climate, and additionally to better address whether the computationally expensive procedure of dynamical downscaling is necessary to assess changes in severe storms.

In Chapter 2, the response of future convective environments as projected by GFDL-CM3 was investigated for two separate climate change scenarios: RCP4.5, the mid-range mitigation scenario, and the most aggressive RCP8.5 scenario. It was found that the two climate projections begin to significantly diverge from one another after 2050, due likely to the more robust increases in CAPE by RCP8.5 beyond that point.
The distinction between the two projections emerge primarily within the projected magnitude of increase for several HCW parameters studied, as similar spatial areas of enhanced HCW environment day frequency are highlighted. The greatest increases in days with favorable HCW environments materialized during the spring and summer months, though strong relative increases were noted during DJF in the southeastern United States. The elevated frequency of potentially severe environments is largely attributed to robust increases in CAPE, in accordance with previous work in this area. A finding not strongly emphasized by many recent studies, though previously suggested, is the tendency for favorable environments to transpire both earlier and later in the annual cycle, thereby implying a potential lengthening of the severe weather season. Further, it was found that future occurrences of severe environment days demonstrated a tendency toward both increasing intensity and areal coverage.

Results from the regional climate simulations produced by downscaling the GFDL-CM3 historical and RCP8.5 projections for 1971–2000 and 2071–2100 were presented in Chapter 3. Two variables, hourly maximum updraft helicity (maxUH) and upward vertical velocity (UVV) exceeding specified thresholds, were utilized as surrogates for any HCW event. The former allows for a means to identify rotating storms while the latter measures the updraft strength, a measure of storm intensity. In this way, analysis of the changes in occurrence and intensity of these proxy variables allowed for a way to gauge the storm-scale response of the altered large-scale environmental conditions. Similar to the environment projections, the greatest increases in activity were noted in DJF in the southeastern U.S., much of the U.S. east of the Rocky Mountains during the spring months (MAM), and in the northern Plains during JJA. Further, several additional proxies were explored in an attempt to gain understanding into potential influences a warming climate may have upon individual storm hazards (i.e., tornadoes, wind, and hail events). Inferences drawn from the analysis of these variables (AFWAtor, AFWAhail, maxGRPL, and maxWIND) suggest that all hazards may become more frequent in the spring and summer, with perhaps a shift toward higher intensity. At the same time, the signal during DJF features a greater wind
and tornado threat, while the autumn primarily infers a only an augmentation of wind and hail. It is cautioned that these results are highly experimental, and further investigation into their association with observed severe events is advocated. Moreover, the evaluation of the annual cycle of HCW environments provides evidence that the severe thunderstorm season may be lengthened in future climate, though the annual occurrence frequency displayed a propensity for greater interannual variability, a result that bolsters the findings of Gensini and Mote (2015).

Lastly, Chapter 4 probed the relationship between favorable severe weather environment days and occurrences of severe event days within the downscaled simulations. In general, the spatial patterns are strongly correlated, with the exception of autumn, such that it lends support for using the environmental approach to assess the location and seasonal timing of projected changes in HCW days. However, the magnitude of change is much more difficult to gauge solely on the basis of favorable HCW environments. According to these simulations, it has become apparent that relationship between the environment and event has been altered, and that the HCW favorable environments alone cannot infer HCW occurrence. These results may be indicative that some change in the larger scale forcing has occurred which has affected the rate at which storms are realized within otherwise favorable conditions. This revelation, although speculated as a potential hindrance to the environmental interpretation (e.g., Diffenbaugh et al., 2013; Seeley and Romps, 2015), has not been directly shown until now. Though speculation as to several factors that may be contribute to both the enhanced variability in HCW activity and the weakened environment-event relationship, further analysis is needed to offer more conclusive evidence. Such analyses may include investigation into extratropical storm tracks and other forcing mechanisms, such as fronts and drylines, and how their frequency and characteristics in future climate may be attributed to the results found within this study.

Admittedly, the trajectory of change in environments favorable to HCW vary between GCMs, such an ensemble approach is desired to determine the robustness of the climate change signal. Due to the immense computational expense of such an
undertaking, producing a collection of convection-permitting regional climate simulations guided by various GCMs is currently not feasible. The work presented herein represents only one possible solution of the spatiotemporal changes of HCW. Despite this fact, the results within this study provides some insight as to how HCW activity may be modified given certain changes in large-scale convective environments in an anthropogenically altered climate. Though a longer time-slice of simulations is desired for testing statistical significance, future work may explore whether or not a shorter duration of simulations may present similar results, particularly in regards to the relationship between environmental conditions and simulated events. Should a shorter time period be found to be sufficient, computational resources may be preserved, or even allocated toward performing an ensemble of regional climate simulations.

To conclude, while not the first to use WRF at convective-permitting resolution for the purpose of investigating the HCW-climate change connection, this work is novel in that the regional climate simulations performed encapsulate the entire annual cycle and the duration of time-slice experiments for the historical and future climatological periods have been extended beyond that of previous studies (to 30 years). Additionally, investigation of climate change impacts upon specific severe thunderstorm hazards has mostly been unexplored until this work. By and large, this study adds to the growing body of evidence to support the conclusion that unabated warming of the climate system may lead to a greater frequency in severe storms in the future in the contiguous United States. As a final acknowledgment, it is contended that the compiled dataset may be useful for researchers from a broad range of disciplines (e.g., hydrology, ecology, agriculture, economics, etc.) interested in studying other localized climate change impacts beyond the focus of this study.
REFERENCES
REFERENCES


APPENDICES
APPENDIX A. SUPPLEMENTARY FIGURES FOR CHAPTER 2

Figure A.1. Mean seasonal changes in MLCAPE days (a)–(b) DJF, (c)–(d) MAM, (e)–(f) JJA, and (g)–(h) SON compared to the historical period. RCP4.5 differences are depicted in (a),(c),(e), and (g) while RCP8.5 are depicted in (b),(d),(f), and (h).
Figure A.2. Mean seasonal changes in near-surface temperature (K) for (a)–(b) DJF, (c)–(d) MAM, (e)–(f) JJA, and (g)–(h) SON compared to the historical period. RCP4.5 differences are depicted in (a),(c),(e), and (g) while RCP8.5 are depicted in (b),(d),(f), and (h).
Figure A.3. As in Figure A.2 except for near-surface specific humidity ($gkg^{-1}$).
Figure B.1. Mean MAM and JJA seasonal changes in days with maxUH ≥ (a),(b) 75, (c),(d) 100, and (e),(f) 150 m²s⁻².
Figure B.2. Mean MAM and JJA seasonal changes in days with UVV $\geq$ (a),(b) 30, (c),(d) 35, and (e),(f) 40 ms$^{-1}$. 
Figure B.3. Mean MAM and JJA seasonal changes in days with REFC $\geq$ 60 dBZ.
Figure B.4. 30-year mean probability of experiencing $\text{maxUH} \geq 50$ within the (a) Midwest, (b) Northeast, (c) Southeast, (d) Southern Plains, (e) Northern Plains, and (f) West regions according to Julian date. The raw probabilities are represented by the scatter points, and a Gaussian filter is applied with $\sigma = 15$ days, as in Brooks et al. (2003a), represented by the bold lines. The historical (1971–2000) and future (2071–2100) periods are represented by the navy and red lines, respectively.
(a) Midwest
(b) Northeast
(c) Southeast
(d) Southern Plains
(e) Northern Plains
(f) West

Figure B.5. As in Figure B.4, except for UVV $\geq 20 \text{ ms}^{-1}$. 
Figure B.6. Daily grid point frequency of maxUH $\geq 50 \text{ m}^2\text{s}^{-2}$ for the (a) Midwest, (b) Northeast, (c) Southeast, (d) Southern Plains, (e) Northern Plains, and (f) West regions. Raw sums have been smoothed with a Gaussian filter ($\sigma=15$ days) The mean daily frequency values for the historical (future) period are represented by the solid (dashed) black lines.
Figure B.7. As in Figure B.6, except for UVV $\geq 20 \, ms^{-1}$.
Figure B.8. Mean annual number of days with (a) AFWA_{tor} ≥ 50 \text{ ms}^{-1}, (b) AFWA_{hail} ≥ 50 \text{ mm}, (c) maximum column integrated graupel ≥50 \text{ kgm}^{-2}, and (d) hourly maximum 10 m wind speed ≥30 \text{ ms}^{-1} (in the presence of at least 40 dBZ reflectivity at 1 km AGL).
Figure B.9. Mean DJF, MAM and JJA seasonal changes in days with AFWAtor $\geq (a),(c),(e) 40$ and $(b),(d),(f) 50 \text{ ms}^{-1}$.
Figure B.10. Mean MAM and JJA seasonal changes in days with maxGRPL ≥ (a),(b) 35, (c),(d) 50 kgm$^{-2}$.

Figure B.11. Mean MAM and JJA seasonal changes in days with AFWAhail ≥ (a),(b) 35, and (c),(d) 50 mm.
APPENDIX C. SUPPLEMENTARY FIGURES FOR CHAPTER 4

Figure C.1. Linear regression between U.S. (east of -105°W; land points only) monthly mean (a) \( NDSEV_{1.6} \), (b) \( NDSEV \), (c) \( NDSEV_{tor} \), and (d) \( STP \) days with monthly mean days with \( \text{maxUH} \geq 50 \text{ m}^2\text{s}^{-2} \). Monthly mean HCW environment days for each of the 30-years of historical (1971–2000; navy line and scatter points) and future (2071–2100; maroon line and scatter points) periods serve as the predictors. Bootstrapped 95% confidence intervals are shaded.
Figure C.2. As in Figure C.1, except for days with UVV $\geq 20 \text{ ms}^{-1}$.
Figure C.3. Linear regression between regional mean $NDSEV_{sig}$ and maxUH ($\geq 50 \text{ m}^2\text{s}^{-2}$) days for the (a) Midwest, (b) Northeast, (c) Southeast, (d) Southern Plains, (e) Northern Plains, and (f) West regions. Monthly mean HCW environment days for each of the 30-years of historical (1971–2000; navy line and scatter points) and future (2071–2100; maroon line and scatter points) periods serve as the predictors. Bootstrapped 95% confidence intervals are shaded for each line.
Figure C.4. As in Figure C.3, except for days with UVV $\geq 20$ ms$^{-1}$. 

(a) Midwest

(b) Northeast

(c) Southeast

(d) Southern Plains

(e) Northern Plains

(f) West
Figure C.5. Linear regression between U.S. (east of -105°W; land points only) monthly mean \(NDSEV_{\text{sig}}\) with monthly mean days with max\(UH\geq50\ m^2s^{-2}\) for (a) DJF, (b) MAM, (c) JJA, and (d) SON. Monthly mean HCW environment days per season for each of the 30-years of historical (1971–2000; navy line and scatter points) and future (2071–2100; maroon line and scatter points) periods serve as the predictors. Bootstrapped 95% confidence intervals are shaded.
Figure C.6. As in Figure C.3, except for days with UVV $\geq 20$ ms$^{-1}$. 

(a) DJF  
(b) MAM  
(c) JJA  
(d) SON
APPENDIX D. DATA INFORMATION AND GRIB2 TABLE

Table D.1 specifies the pertinent parameters needed to decode the grib2 data from the regional climate simulations correctly. Additionally, as the WRF simulations do not account for leap year, the encoded forecast hour for data that fall on leap years was modified. Specifically, March 1st (0000–1200Z) data will have incorrect forecast hour data (F42–F54) instead of F18–F30 due to the way the Unified Post Processor handles dates for leap year.

Listed below are the current known issues with the generated data:

• Specific humidity values are not correct, due to an error in compression specification upon data
• AFWA hail size coded with units of m (data in mm)
• Surface wind gust coded as 10 m wind gust
Table D.1: Grib2 Encoding Details

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<th>Discipline</th>
<th>Parm.</th>
<th>Category</th>
<th>Parm. Number</th>
<th>Fixed Surface</th>
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VITA

Kimberly Anne Hoogewind was born in Grand Rapids, MI on September 8, 1984, to parents Ken and Peggy Hoogewind. She is sister to twin brother Michael, brother Christopher, and sister Shelly. Upon graduating from Lowell High School in 2003, Kimberly completed coursework at Western Michigan University and Grand Rapids Community College before transferring to Central Michigan University in 2006 to pursue a degree in meteorology. While at CMU, she completed undergraduate research under the supervision of Dr. Martin Baxter and served as a student volunteer at the Grand Rapids, MI National Weather Service forecast office. In the spring of 2009, Kimberly graduated magna cum laude with a B.S. in Meteorology, and subsequently began her graduate studies in Fall of 2009 at Purdue University.

While at Purdue, Kimberly was a Student Career Experience Program (SCEP) intern with the National Weather Service and served as graduate student representative on the Unidata Users Committee. Kimberly developed a strong interest in teaching, where she volunteered as a graduate team leader for the Innovation to Reality (I2R) after school program for middle school students to learn about natural disasters, helped to facilitate graduate teaching assistant orientation session, and worked as a student-athlete tutor and teaching assistant. She received the Committee for the Education of Teaching Assistants (CETA) Teaching Excellence Award in acknowledgment of her teaching efforts. Kimberly completed her M.S. degree in May of 2012, and continued on to pursue doctoral studies. In February of 2016, she successfully defended her Ph.D. dissertation and subsequently began a postdoctoral research appointment at the University of Illinois at Urbana-Champaign.